The discourse of propaganda:
language strategies analysed with NLP methods

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Supervision
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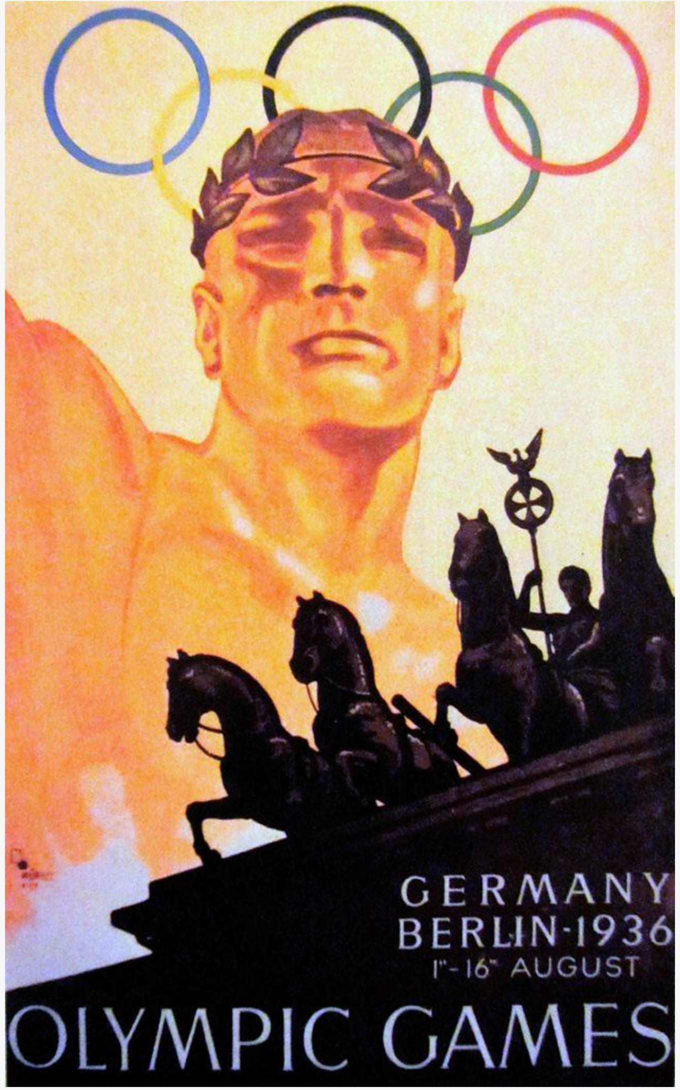
Agenda

- Propaganda and its language
- Existing approaches
- Overview of methodology
- Results

Propaganda and its language

Definition of propaganda

- The term Propaganda originates from the Catholic Church.
    - In the 16th century
    - the phrase *Congregatio de propaganda fide* (Merriam Webster, 2024)
- The term became widespread after World War II.
- Nazi War Machine in the Ministry of Propaganda (ger. Propagandaministerium) (CIA and Committee For National Morale, 1942)



https://ichef.bbci.co.uk/images/ic/640xn/p03hdhbb.jpg

Language used in propaganda 1/5

Appeal to Authority

Appeal to Fear/Prejudice

Bandwagon

Black-and-White Fallacy

Language used in propaganda 2/5

Causal Oversimplification

Doubt

Exaggeration or Minimization

Flag-Waving

Language used in propaganda 3/5

- Loaded Language
- Name Calling
- Red Herring
- Reductio ad Hitlerum

Language used in propaganda 4/5

- **Repetition**
- **Slogans**
- **Straw Man**
- **Thought-Terminating Cliché**

Language used in propaganda 5/5

Labelling

Whataboutism

Existing approaches

Existing approaches: ***Proppy*** (Barrón-Cedeño i in., 2019)

Step 1: News Retrieval

Step 2: Clustering by Event

Step 3: De-duplication

Step 4: Propaganda Index Computation

Existing approaches: ***Propaganda Detection Using Sentiment Aware Ensemble Deep Learning*** (Polonijo i in., 2021)

IDEA

DATASET

VARIABLES

RESULTS

KEY FINDINGS

Existing approaches: ***Fine-Grained Propaganda Detection with Fine-Tuned BERT*** (Yoosuf & Yang, 2019)

Overview

Methodology

Results

Key findings

Existing approaches: ***Large Language Models for Propaganda Detection*** (Sprenkamp i in., 2023)

Overview

Methodology

Dataset

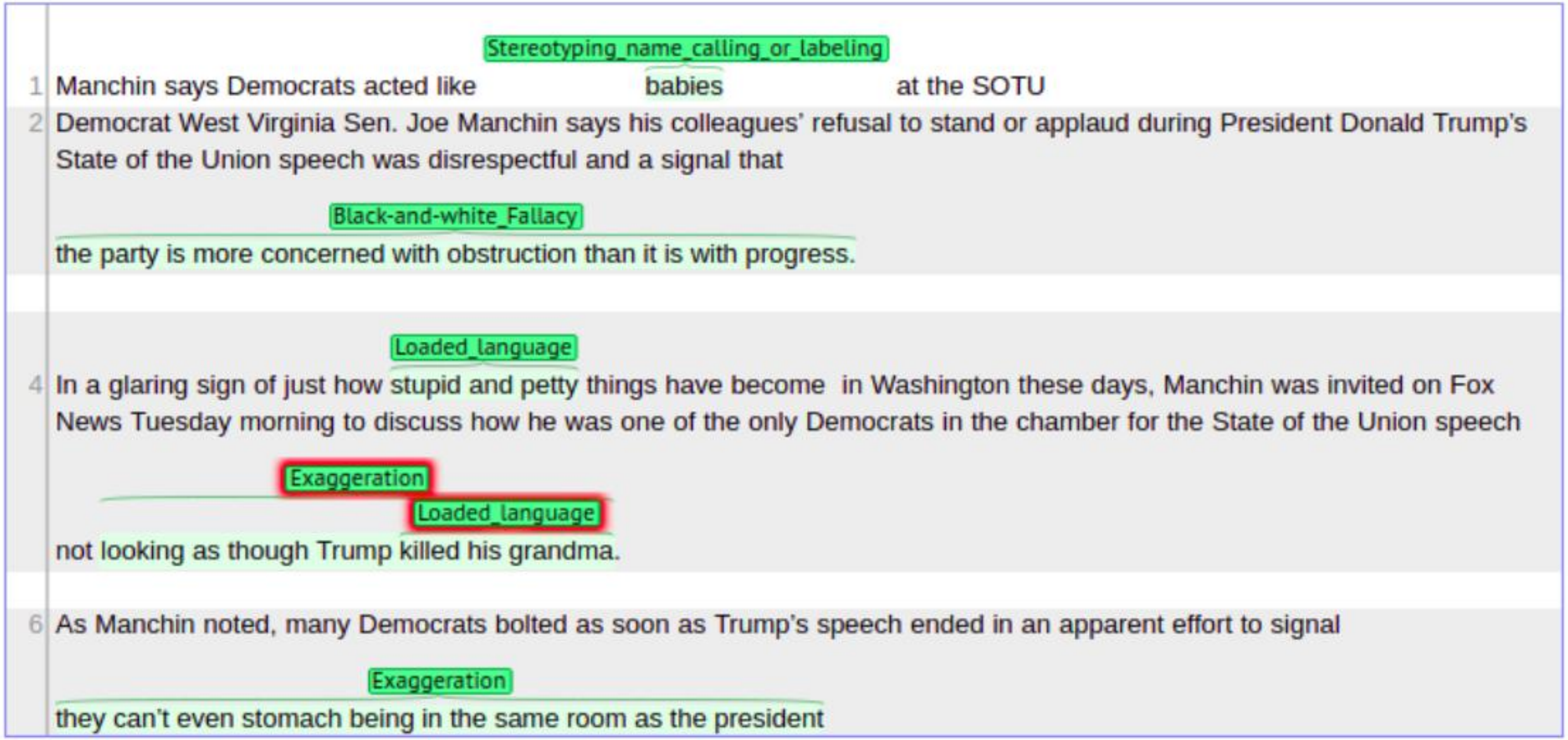
Results

Overview of methodology

Goal

Create an approach for **span identification** of propaganda techniques using **LLMs**

Goal



https://aclanthology.org/D19-5024.pdf

Dataset

samples

- **Original**
  - 350 train – only this available
  - 61 dev
  - 86 test
- **Ours:** 250 train, 25 dev (validation), 75 test

Dataset

technique stats

Technique	Number of articles
Appeal_to_Authority	70
Appeal_to_fear-prejudice	135
Bandwagon	11
Black-and-White_Fallacy	65
Causal_Oversimplification	98
Doubt	156
Exaggeration, Minimisation	177
Flag-Waving	126
Loaded_Language	296
Name_Calling, Labeling	206
Obfuscation, Intentional_Vagueness, Confusion	10
Red_Herring	23
Reductio_ad_hitlerum	35
Repetition	147
Slogans	75
Straw_Men	10
Thought-terminating_Cliches	66
Whataboutism	38

Technique	Number of occurances
Appeal_to_Authority	156
Appeal_to_fear-prejudice	288
Bandwagon	16
Black-and-White_Fallacy	135
Causal_Oversimplification	243
Doubt	611
Exaggeration, Minimisation	487
Flag-Waving	252
Loaded_Language	2,137
Name_Calling, Labeling	1,090
Obfuscation, Intentional_Vagueness, Confusion	13
Red_Herring	36
Reductio_ad_hitlerum	59
Repetition	580
Slogans	139
Straw_Men	14
Thought-terminating_Cliches	83
Whataboutism	62

Dataset
split

	Sample		
Technique	train	val	test
Appeal_to_Authority	98	19	39
Appeal_to_fear-prejudice	196	29	63
Bandwagon	6	4	6
Black-and-White_Fallacy	78	14	43
Causal_Oversimplification	179	30	34
Doubt	463	40	108
Exaggeration,Minimisation	349	51	87
Flag-Waving	173	21	58
Loaded_Language	1,558	156	423
Name_Calling,Labeling	816	76	198
Obfuscation,Intentional_Vagueness,Confusion	11	0	2
Red_Herring	22	2	12
Reductio_ad_hitlerum	48	1	10
Repetition	457	21	102
Slogans	107	6	26
Straw_Men	14	0	0
Thought-terminating_Cliches	46	5	32
Whataboutism	45	5	12

	Sample		
Technique	train	val	test
Appeal_to_Authority	2.1%	3.96%	3.11%
Appeal_to_fear-prejudice	4.2%	6.04%	5.02%
Bandwagon	0.13%	0.83%	0.48%
Black-and-White_Fallacy	1.67%	2.92%	3.43%
Causal_Oversimplification	3.84%	6.25%	2.71%
Doubt	9.92%	8.33%	8.61%
Exaggeration,Minimisation	7.48%	10.62%	6.93%
Flag-Waving	3.71%	4.38%	4.62%
Loaded_Language	33.39%	32.5%	33.71%
Name_Calling,Labeling	17.49%	15.83%	15.78%
Obfuscation,Intentional_Vagueness,Confusion	0.24%	0.0%	0.16%
Red_Herring	0.47%	0.42%	0.96%
Reductio_ad_hitlerum	1.03%	0.21%	0.8%
Repetition	9.79%	4.38%	8.13%
Slogans	2.29%	1.25%	2.07%
Straw_Men	0.3%	0.0%	0.0%
Thought-terminating_Cliches	0.99%	1.04%	2.55%
Whataboutism	0.96%	1.04%	0.96%

Dataset - example

"article": "US bloggers banned from entering UK\n\nTwo prominent US bloggers have been banned from entering the UK, the Home Office has said.
\n\nPamela Geller and Robert Spencer co-founded anti-Muslim group Stop Islamization of America.\n\nThey were due to speak at an English
Defence League march in Woolwich, where Drummer Lee Rigby was killed.\n\nA government spokesman said individuals whose presence \"is not
conducive to the public good\" could be excluded by the home secretary.\n\nHe added: \"We condemn all those whose behaviours and views run
counter to our shared values and will not stand for extremism in any form.\"\n\n'Right decision'\nMs Geller, of the Atlas Shrugs blog, and Mr
Spencer, of Jihad Watch, are also co-founders of the American Freedom Defense Initiative, best known for a pro-Israel \"Defeat Jihad\" poster
campaign on the New York subway.\nOn both of their blogs the pair called their bans from entering the UK \"a striking blow against freedom\"
and said the \"the nation that gave the world the Magna Carta is dead\".\n\nThey were due to attend a march planned by the far-right EDL to
mark Armed Forces Day on 29 June, ending in Woolwich, south east London, where soldier Drummer Rigby was murdered last month.\n\nKeith Vaz,
chairman of the Home Affairs Select Committee, who had called for the bloggers to be banned from the UK, said: \"I welcome the home
secretary's ban on Pamela Geller and Robert Spencer from entering the country.\nThis is the right decision.\nThe UK should never become a
stage for inflammatory speakers who promote hate.\"\n\nEDL leader Tommy Robinson, meanwhile, criticised the decision and said Ms Geller and Mr
Spencer were coming to the UK to lay flowers at the place where Drummer Rigby died.\n\n\"It's embarrassing for this so-called land of
democracy and freedom of speech,\" he said.\n\n\"How many hate preachers are living in this country?\nIt just shows what sort of a two-tier
system we have here.\"\n\n'Foster hatred'\nAnti-fascism campaigners Hope Not Hate had campaigned for the pair to not be allowed into the UK.
\n\nA researcher with the organisation, Matthew Collins, said it was \"delighted\" with the decision.\n\n\"These two are among some of the
most extreme anti-Muslim activists in the world.\nThey've nothing to contribute to life in this country.\n\n\"They're not here to contribute
to good community relations.\nThey only wanted to come here and help the EDL stir up more trouble.\nBritain doesn't need more hate even just
for a few days.\"\n\nMr Spencer put up a copy of what appears to be the exclusion decision from the Home Office on the Jihad Watch website,
while Ms Geller posted a copy of her letter on her website, Atlas Shrugs.\n\nThe letters, both dated Tuesday, claim that both activists have
fallen within the scope of a list of unacceptable behaviours by making statements which may \"foster hatred\" and lead to \"inter-community
violence\" in the UK.\n\nBoth letters gave examples of anti-Muslim views stated by both and went on to say that should they be allowed to
enter the UK the home secretary believes they would \"continue to espouse such views\".\n",

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{
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    "start": 958,
    "end": 1013,
    "excerpt": "the nation that gave the world the Magna Carta is dead",
    "sentence_numbers": [
        15
    ],
    "affected_sentences": [
        "On both of their blogs the pair called their bans from entering the UK \"a striking blow against freedom\" and said the \"the
        nation that gave the world the Magna Carta is dead\"."
    ]
},

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HOW WILL IT WORK

- Ask a question
  - Technique name
  - Excerpt
  - Sentence


```
[ParsedChatCompletionMessage[NoneType](content='1. Technique: Name_Calling,Labeling\n   Excerpt: "a weak
sister"\n   Sentence: "Sessions is a weak sister."\n\n2. Technique: Loaded_Language\n   Excerpt: "He has
to go."\n   Sentence: "He has to go."\n\n3. Technique: Exaggeration,Minimisation\n   Excerpt: "This
leftwing witch hunt has been ongoing since day one of Trump's presidency"\n   Sentence: "This leftwing
witch hunt has been ongoing since day one of Trump's presidency in order to impair and impede his ability
to get the job done."\n\n4. Technique: Loaded_Language\n   Excerpt: "a stealth coup."\n   Sentence: "It's
a stealth coup."\n\n5. Technique: Name_Calling,Labeling\n   Excerpt: "a weak sister"\n   Sentence:
"Sessions is a weak sister."\n\n6. Technique: Exaggeration,Minimisation\n   Excerpt: "He has to go."\n
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```

HOW WILL IT WORK - parsing


```
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to get the job done."\n\n12. Techniq
"It’s a stealth coup."\n\n13. Techni
"Sessions is a weak sister."\n\n14.
```

```
[Technique(technique_name='Loaded_Language', technique_excerpt='blessing of gay couples', sentence_of_technique='Austrian diocese blesses gay couples on Valentine’s Day, makes reference to Amoris Laetitia'),

 Technique(technique_name='Name_Calling,Labeling', technique_excerpt='gay couples', sentence_of_technique="The Diocese of Linz, Austria, invited homosexual couples to participate in the blessing of couples on St. Valentine's Day."),

 Technique(technique_name='Loaded_Language', technique_excerpt="the German bishops' initiative to bless homosexual couples,", sentence_of_technique="The move comes in the wake of the recent debate over the German bishops' initiative to bless homosexual couples, as well as the controversy over Bishop Andreas Laun's own criticism of it."),

 Technique(technique_name='Loaded_Language', technique_excerpt='the diocesan newspaper', sentence_of_technique='As is explained in the article:'),

 Technique(technique_name='Name_Calling,Labeling', technique_excerpt='homosexual couples', sentence_of_technique='St. Valentine is known as the saint of friendship and of love.'),

 Technique(technique_name='Loaded_Language', technique_excerpt='an enormous power”', sentence_of_technique="Irmgard Lehner, the pastoral assistant of the Wels-St. Franziskus Church, the other of the two parishes that welcome homosexual couples, appreciates this blessing ritual for Valentine's Day, saying it has “an enormous power.” During the ceremony, couples come forward in church and receive a hand on their foreheads and a sign of the cross."),

 Technique(technique_name='Loaded_Language', technique_excerpt='a clear signal', sentence_of_technique='It would be good if a clear sign of openness and invitation would be made by many more pastoral workers [male and female], in order to give the clear signal that love between two persons with equal rights are wished by God and thus already blessed.'),

 Technique(technique_name='Loaded_Language', technique_excerpt='a high-ranking priest', sentence_of_technique='As LifeSiteNews reported in January, the Diocese of Limburg is publicly discussing the establishment of a special liturgical rite for the blessing of homosexuals.'),

 Technique(technique_name='Loaded_Language', technique_excerpt='moral turmoil', sentence_of_technique='This moral turmoil in German dioceses has provoked concern and criticism among Catholics.')]
```

Approach to detection

- **Using local LLMs**
  - **without examples (zero-shot)**
  - with some examples (few-shot)
  - one or more techniques per query
- **Fine-tuning (LORA)**

LoRA (Hu et al., 2021) - Benefits

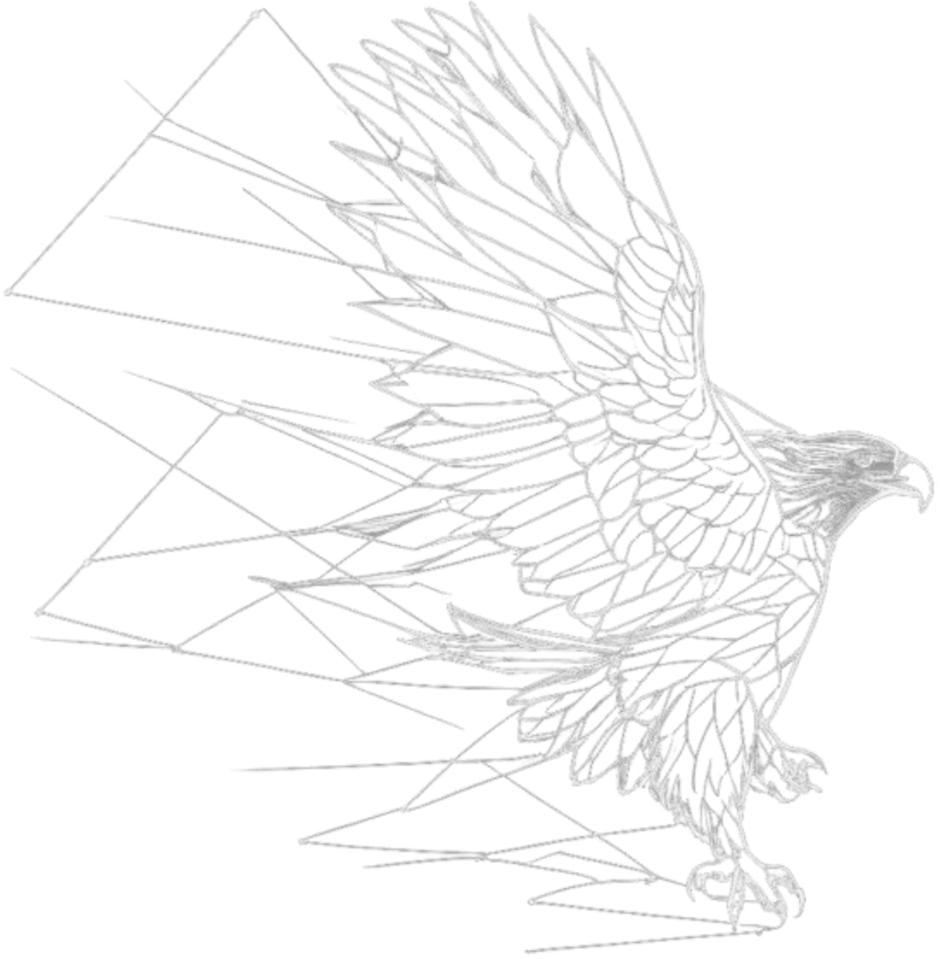
Memory Efficiency: ~95% fewer trainable parameters

Storage Efficient: Adapters typically <100MB vs. full models (100GB+)

Adaptability: Multiple LoRA adapters can be swapped for different tasks

Which models?

- ~~**speakleash/Bielik-11B-v2.3-Instruct**~~
  - ~~Good quality of both Polish and English language~~
- **unsloth/gemma-2-9b**
  - Good quality in NER (Named Entity Recognition) tasks



https://bielik.ai/

So which models in the end?

- unsloth/gemma-2-9b-4bit-bnb
- unsloth/gemma-2-2b
- unsloth-llama-3.2-3b-instruct
- unsloth-mistral-7b-ins-v0-3-bnb-4bit

Approach

Ask a question

Parse

Validate

Validation

If no response from NLP4IF-2019 authors

- Own models
  - Train-test-val split of 250-75-25
- SOTA
  - Run the training script from winner's GitHUB

Otherwise

- Own models
  - Train-test-val split as defined in the paper
- SOTA
  - Compare to winner's paper

Validation – final method

If no response from NLP4IF-2019 authors

- Own models
  - Train-test-val split of 250-75-25
- SOTA
  - Run the training script from winner’s GitHUB

Experiments – picking the best model

Explore grid of epochs/LoRA ranks

Pick the best one on validation set (across 3 runs)

Metrics

Document Representation

- Given a document d as a sequence of characters
- Let $t = [t_n, \dots, t_m]$ be a fragment of d containing a named entity
- Let $s = [s_i, \dots, s_j]$ be a fragment predicted by the model

Definitions

- T: Set of gold-truth fragments (may have overlaps)
- S: Set of predicted fragments
- $l(x) \in \{1, \dots, n_{classes}\}$: Function assigning a class to fragment x
- $\delta(a, b)$: Function equal to 1 when $a = b$, 0 otherwise

$$C(s,t,h) = \frac{|(s \cap t)|}{h} \delta(l(s), l(t))$$

$$F1 \begin{cases} P(S,T) = \dfrac{1}{|S|} \displaystyle\sum_{s \in S, t \in T} C(s,t,|s|) \\[2ex] R(S,T) = \dfrac{1}{|T|} \displaystyle\sum_{s \in S, t \in T} C(s,t,|t|) \end{cases}$$

Initial results

SOTA:
F1 ~ 0.231

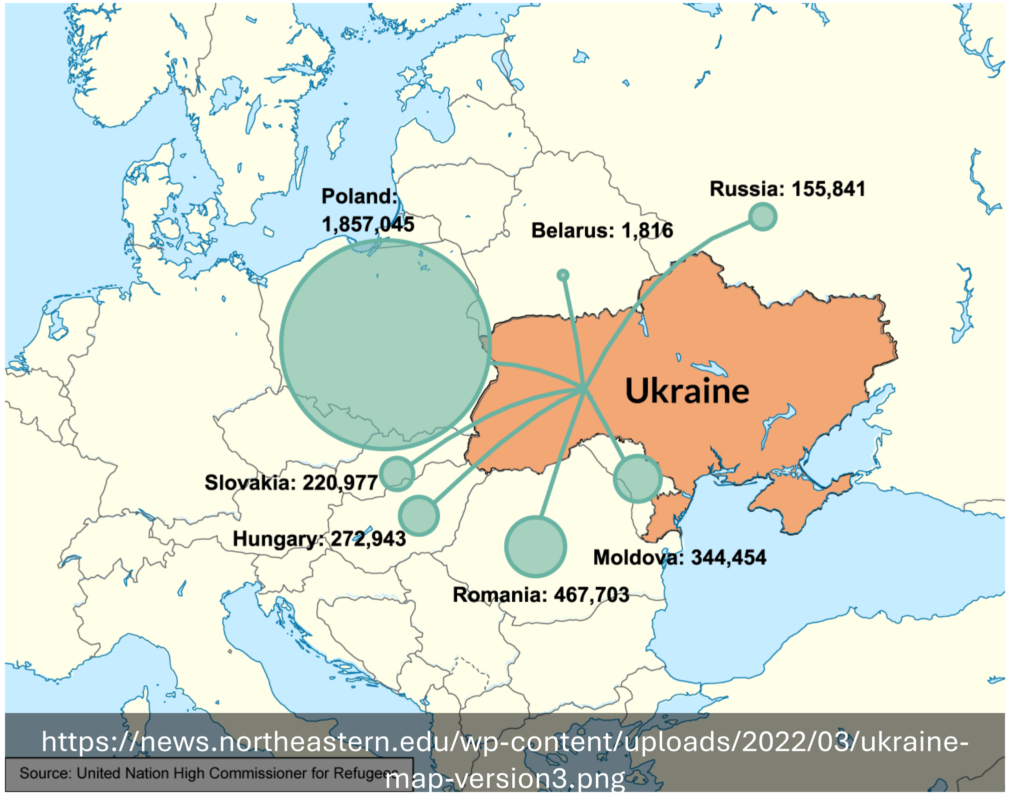
Few Shot, without LoRA:
F1 ~ 0.034

Zero Shot, with LoRA:
F1 ~ 0.17

Key analyses and questions

Problem of migration

- Migration and immigrants appear as a significant socio-political factor [Schneider-Strawczynski & Valette, 2023]
- More than 26 million border crossings from Ukraine to Poland have been recorded [United Nations High Commissioner for Refugees, 2025]



https://news.northeastern.edu/wp-content/uploads/2022/03/ukraine-map-version3.png

Data to be analysed

SPEECHES FROM THE POLISH GOVERNMENT (SEJM) FROM THE LAST 8-10 YEARS

POLISH NEWS OUTLETS

TIKTOK™ ACCOUNTS RELATED TO POLITICS

How scraping works

Sejm

official API

News sites

dedicated scrapers in Selenium

TikTok

unofficial API

Research questions

How has the language of propaganda regarding migration evolved over the last 10 years in Poland?

What are the patterns of propaganda and sentiment towards immigrants in Polish media?

How does the portrayal of immigrants on TikTok differ from traditional media platforms in Poland?

Techniques in propaganda vs techniques themselves

Create a small dataset

Validate behaviour of techniques in propaganda vs non-propaganda context

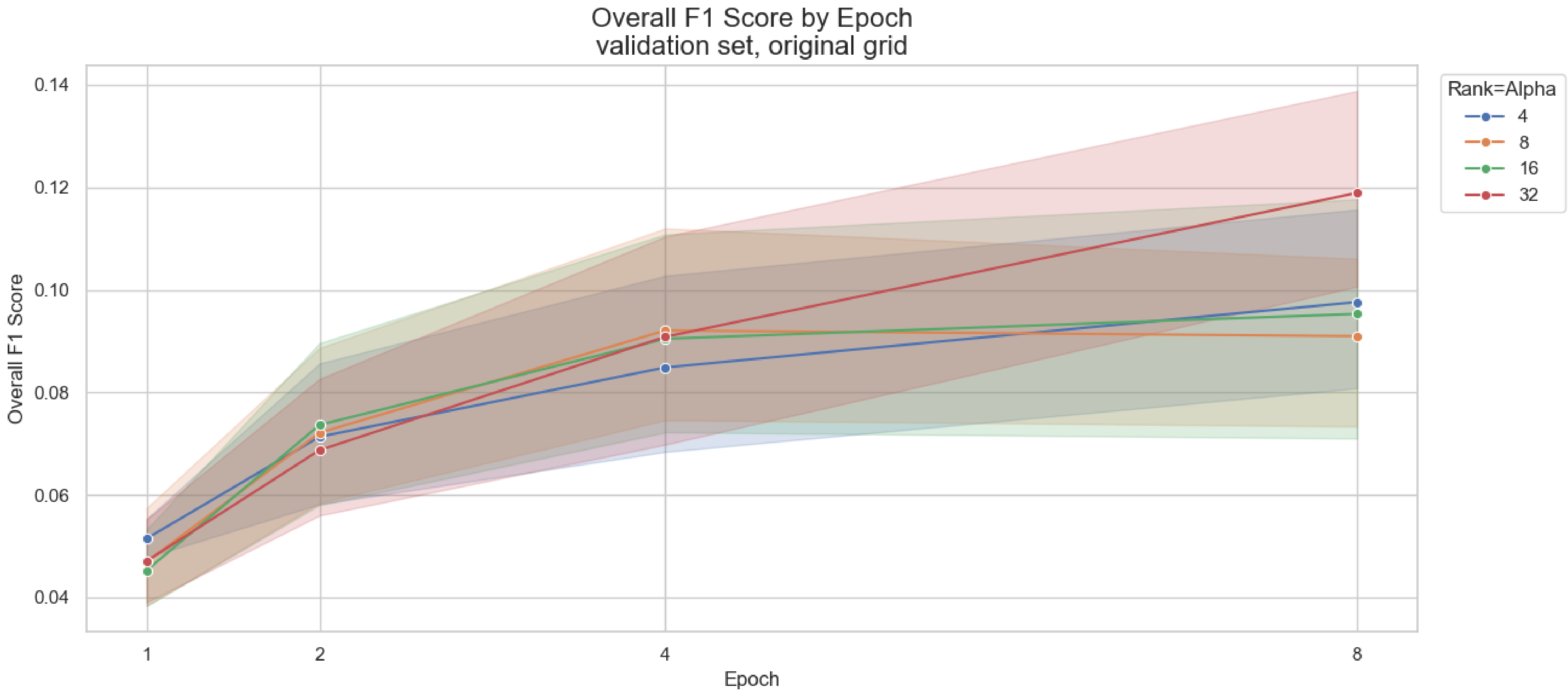
Results

Hyperparameters
validation set

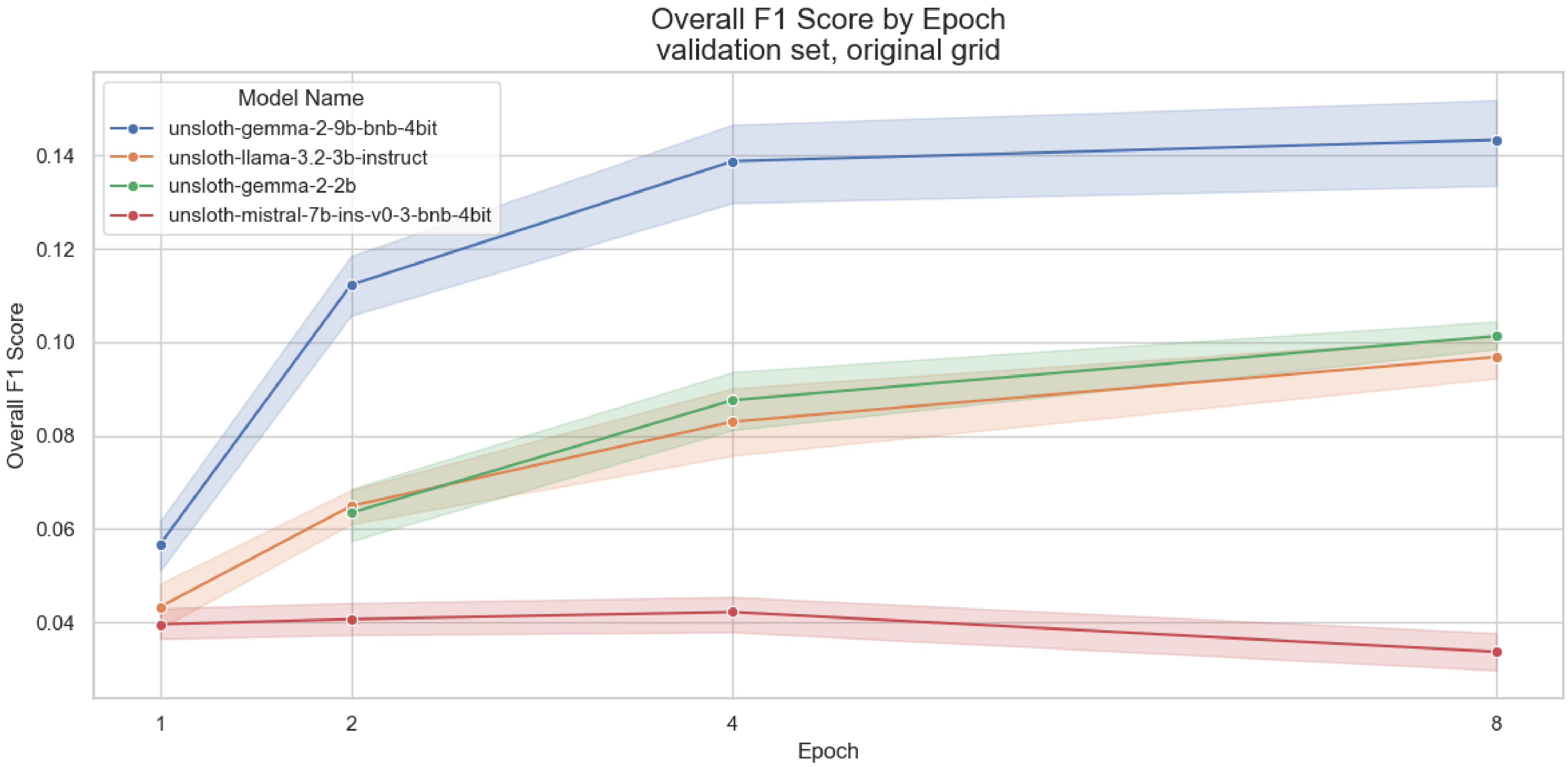
Scaling factor (alpha):
4, 8, 16, 32

Epochs:
1, 2, 4, 8

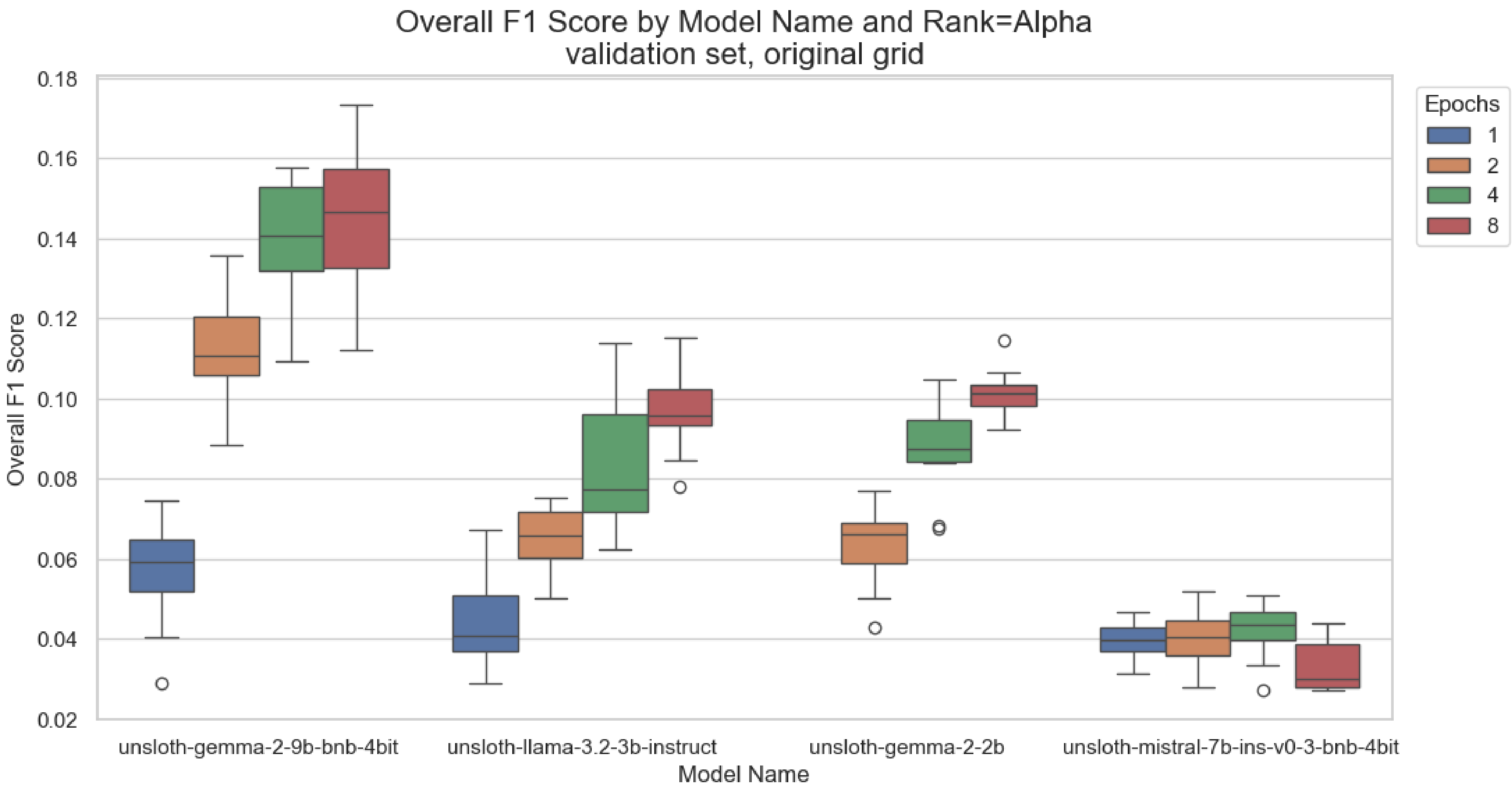
Score vs epoch, by rank
Validation set



Score vs epoch, by model
Validation set



Score vs model, by epoch
Validation set



Score vs model, by rank
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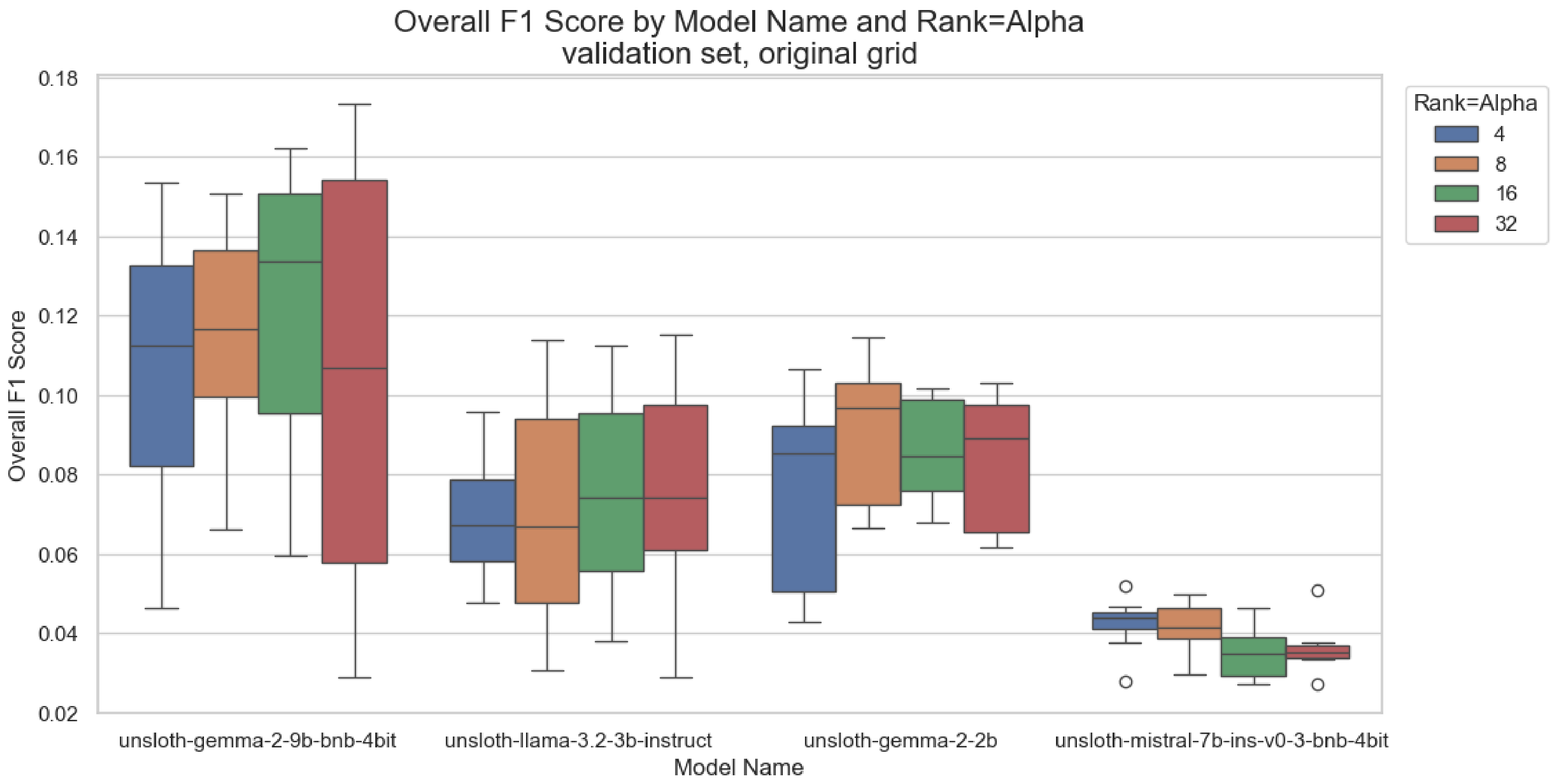


10 best models/parameters

validation set, 3 runs

			Overall F1				Binary F1				Number of failed chunks			
model_name	rank=α	epochs	mean	max	min	std	mean	max	min	std	mean	max	min	std
unsloth-gemma-2-9b-bnb-4bit	32	8	**0.1639**	**0.1732**	**0.1539**	0.0097	0.3234	0.3290	0.3171	**0.0060**	**0.0000**	**0**	**0**	**0.0000**
	16	8	0.1564	0.1621	0.1490	0.0067	**0.3274**	**0.3359**	**0.3178**	0.0091	**0.0000**	**0**	**0**	**0.0000**
	32	4	0.1506	0.1577	0.1396	0.0097	0.2975	0.3058	0.2919	0.0074	1.0000	1	1	**0.0000**
	16	4	0.1455	0.1554	0.1396	0.0086	0.2947	0.3182	0.2828	0.0204	0.3333	1	0	0.5774
	8	4	0.1422	0.1507	0.1316	0.0097	0.2933	0.3035	0.2832	0.0102	**0.0000**	**0**	**0**	**0.0000**
	4	8	0.1388	0.1496	0.1228	0.0141	0.2971	0.3159	0.2816	0.0174	**0.0000**	**0**	**0**	**0.0000**
	1	4	0.1286	0.1533	0.1116	0.0219	0.2745	0.3026	0.2411	0.0311	0.6667	1	0	0.5774
	8	8	0.1214	0.1380	0.1122	0.0143	0.2706	0.2868	0.2507	0.0183	**0.0000**	**0**	**0**	**0.0000**
	1	2	0.1209	0.1358	0.1077	0.0141	0.2464	0.2613	0.2338	0.0139	0.6667	1	0	0.5774
	16	2	0.1180	0.1274	0.1056	**0.0112**	0.2438	0.2522	0.2370	**0.0077**	0.6667	1	0	0.5774

10 best models/parameters
validation set, 3 runs

			Overall F1				Binary F1				Number of failed chunks			
model_name	rank=α	epochs	mean	max	min	std	mean	max	min	std	mean	max	min	std
unsloth-gemma-2-9b-bnb-4bit	32	8	**0.1639**	**0.1732**	**0.1539**	0.0097	0.3234	0.3290	0.3171	**0.0060**	**0.0000**	**0**	**0**	**0.0000**
	16	8	0.1564	0.1621	0.1490	0.0067	**0.3274**	**0.3359**	**0.3178**	0.0091	**0.0000**	**0**	**0**	**0.0000**
	32	4	0.1506	0.1577	0.1396	0.0097	0.2975	0.3058	0.2919	0.0074	1.0000	1	1	**0.0000**
	16	4	0.1455	0.1554	0.1396	0.0086	0.2947	0.3182	0.2828	0.0204	0.3333	1	0	0.5774
	8	4	0.1422	0.1507	0.1316	0.0097	0.2933	0.3035	0.2832	0.0102	**0.0000**	**0**	**0**	**0.0000**
	4	8	0.1388	0.1496	0.1228	0.0141	0.2971	0.3159	0.2816	0.0174	**0.0000**	**0**	**0**	**0.0000**
	1	4	0.1286	0.1533	0.1116	0.0219	0.2745	0.3026	0.2411	0.0311	0.6667	1	0	0.5774
	8	8	0.1214	0.1380	0.1122	0.0143	0.2706	0.2868	0.2507	0.0183	**0.0000**	**0**	**0**	**0.0000**
	1	2	0.1209	0.1358	0.1077	0.0141	0.2464	0.2613	0.2338	0.0139	0.6667	1	0	0.5774
	16	2	0.1180	0.1274	0.1056	**0.0112**	0.2438	0.2522	0.2370	**0.0077**	0.6667	1	0	0.5774

`unsloth-gemma-2-9b-bnb-4bit` is clearly the best

Trends

Higher rank
better performance

More epochs
better performance

Let’s expand the grid

Hyperparameters

validation set

Scaling factor (alpha):
4, 8, 16, 32, 64

Epochs:
1, 2, 4, 8, 12, 16, 20

10 best parameters
validation set, unsloth-gemma-2-9b-bnb-4bit, 3 runs

			Overall F1				Binary F1				Number of failed chunks			
model_name	rank=α	epochs	mean	max	min	std	mean	max	min	std	mean	max	min	std
unsloth-gemma-2-9b-bnb-4bit	64	12	**0.1876**	**0.1918**	**0.1837**	0.0041	**0.3783**	**0.3833**	**0.3705**	0.0069	**0.0000**	**0**	**0**	**0.0000**
	16	20	0.1750	0.1802	0.1686	0.0059	0.3329	0.3457	0.3219	0.0120	0.3333	1	0	0.5774
	4	20	0.1741	0.1790	0.1664	0.0067	0.3614	0.3744	0.3500	0.0123	**0.0000**	**0**	**0**	**0.0000**
	32	12	0.1739	0.1749	0.1719	**0.0017**	0.3219	0.3248	0.3199	**0.0026**	**0.0000**	**0**	**0**	**0.0000**
	8	20	0.1683	0.1725	0.1649	0.0039	0.3240	0.3307	0.3153	0.0079	**0.0000**	**0**	**0**	**0.0000**
	32	8	0.1639	0.1732	0.1539	0.0097	0.3234	0.3290	0.3171	0.0060	**0.0000**	**0**	**0**	**0.0000**
	64	8	0.1635	0.1708	0.1583	0.0065	0.3451	0.3491	0.3419	0.0037	**0.0000**	**0**	**0**	**0.0000**
	64	20	0.1629	0.1677	0.1594	0.0043	0.3135	0.3245	0.3067	0.0096	**0.0000**	**0**	**0**	**0.0000**
	32	16	0.1592	0.1618	0.1543	0.0042	0.3314	0.3478	0.3172	0.0154	**0.0000**	**0**	**0**	**0.0000**
	64	16	0.1590	0.1709	0.1427	0.0146	0.3270	0.3405	0.3078	0.0170	1.0000	1	1	0.0000

10 best parameters
validation set, unsloth-gemma-2-9b-bnb-4bit, 10 re-runs

			Overall F1				Binary F1				Number of failed chunks			
model_name	rank=α	epochs	mean	max	min	std	mean	max	min	std	mean	max	min	std
unsloth-gemma-2-9b-bnb-4bit	64	12	**0.1842**	**0.1927**	**0.1751**	0.0058	**0.3755**	**0.3851**	**0.3593**	0.0087	**0.0**	**0**	**0**	**0.0000**
	16	20	0.1775	0.1905	0.1710	0.0063	0.3389	0.3612	0.3219	0.0104	0.4	1	0	0.5164
	32	12	0.1772	0.1899	0.1666	0.0069	0.3324	0.3497	0.3158	0.0096	**0.0**	**0**	**0**	**0.0000**
	64	8	0.1746	0.1934	0.1651	0.0088	0.3505	0.3659	0.3379	0.0091	**0.0**	**0**	**0**	**0.0000**
	8	20	0.1742	0.1836	0.1618	0.0074	0.3257	0.3386	0.3162	0.0074	**0.0**	**0**	**0**	**0.0000**
	4	20	0.1684	0.1884	0.1503	0.0117	0.3540	0.3672	0.3375	0.0086	0.1	1	0	0.3162
	64	20	0.1683	0.1795	0.1586	0.0056	0.3248	0.3383	0.3096	0.0087	0.1	1	0	0.3162
	32	8	0.1673	0.1861	0.1486	0.0097	0.3301	0.3408	0.3127	0.0089	**0.0**	**0**	**0**	**0.0000**
	2	16	0.1626	0.1671	0.1570	**0.0031**	0.3345	0.3435	0.3219	**0.0066**	0.1	1	0	0.3162
	64	16	0.1551	0.1739	0.1447	0.0086	0.3241	0.3438	0.3107	0.0123	0.9	1	0	0.3162

10 best parameters

test set, unsloth-gemma-2-9b-bnb-4bit, 5 runs

			Overall F1				Binary F1				Number of failed chunks			
model_name	rank=α	epochs	mean	max	min	std	mean	max	min	std	mean	max	min	std
unsloth-gemma-2-9b-bnb-4bit	64	16	**0.1740**	**0.1792**	**0.1696**	0.0036	0.3002	0.3066	0.2942	0.0058	0.2	1	0	0.4472
	64	8	0.1678	0.1725	0.1606	0.0047	**0.3101**	**0.3155**	**0.3053**	0.0046	**0.0**	**0**	**0**	**0.0000**
	8	20	0.1645	0.1673	0.1605	**0.0030**	0.2915	0.2979	0.2839	0.0051	**0.0**	**0**	**0**	**0.0000**
	32	8	0.1620	0.1690	0.1524	0.0071	0.2977	0.3067	0.2898	0.0068	0.8	1	0	0.4472
	64	12	0.1602	0.1649	0.1563	0.0036	0.2858	0.2907	0.2829	**0.0030**	0.2	1	0	0.4472
	16	20	0.1589	0.1638	0.1518	0.0046	0.2931	0.2974	0.2902	0.0028	**0.0**	**0**	**0**	**0.0000**
	64	20	0.1585	0.1637	0.1531	0.0044	0.2833	0.2939	0.2782	0.0061	0.2	1	0	0.4472
	32	12	0.1462	0.1516	0.1387	0.0049	0.2903	0.3019	0.2832	0.0082	0.2	1	0	0.4472
	32	16	0.1442	0.1486	0.1386	0.0039	0.2776	0.2800	0.2756	**0.0019**	**0.0**	**0**	**0**	**0.0000**
	4	20	0.1331	0.1362	0.1275	0.0037	0.2778	0.2833	0.2633	0.0085	0.6	2	0	0.8944

Choice of best model

$$\text{Score}_i = 0.1 \times \text{ValRank}_i \; + \; 0.9 \times \text{TestRank}_i$$

rank=α	Epochs	Val. Rank	Test Rank	Weighted Score
64	16	10	1	1.90
64	8	4	2	2.20
8	20	5	3	3.20
32	8	8	4	4.40
64	12	1	5	4.60
16	20	2	6	5.60
64	20	7	7	7.00
32	12	3	8	7.50
32	16	9	9	9.00
4	20	6	10	9.60

10 best parameters
test set, unsloth-gemma-2-9b-bnb-4bit, 5 runs

			Overall F1				Binary F1				Number of failed chunks			
model_name	rank=α	epochs	mean	max	min	std	mean	max	min	std	mean	max	min	std
unsloth-gemma-2-9b-bnb-4bit	64	16	**0.1740**	**0.1792**	**0.1696**	0.0036	0.3002	0.3066	0.2942	0.0058	0.2	1	0	0.4472
	64	8	0.1678	0.1725	0.1606	0.0047	**0.3101**	**0.3155**	**0.3053**	0.0046	**0.0**	**0**	**0**	**0.0000**
	8	20	0.1645	0.1673	0.1605	**0.0030**	0.2915	0.2979	0.2839	0.0051	**0.0**	**0**	**0**	**0.0000**
	32	8	0.1620	0.1690	0.1524	0.0071	0.2977	0.3067	0.2898	0.0068	0.8	1	0	0.4472
	64	12	0.1602	0.1649	0.1563	0.0036	0.2858	0.2907	0.2829	**0.0030**	0.2	1	0	0.4472
	16	20	0.1589	0.1638	0.1518	0.0046	0.2931	0.2974	0.2902	0.0028	**0.0**	**0**	**0**	**0.0000**
	64	20	0.1585	0.1637	0.1531	0.0044	0.2833	0.2939	0.2782	0.0061	0.2	1	0	0.4472
	32	12	0.1462	0.1516	0.1387	0.0049	0.2903	0.3019	0.2832	0.0082	0.2	1	0	0.4472
	32	16	0.1442	0.1486	0.1386	0.0039	0.2776	0.2800	0.2756	**0.0019**	**0.0**	**0**	**0**	**0.0000**
	4	20	0.1331	0.1362	0.1275	0.0037	0.2778	0.2833	0.2633	0.0085	0.6	2	0	0.8944

Best model
per technique results – test set

	Support	F1 Score (Overall = Binary)				Precision				Recall			
Propaganda Technique	Test Set	Mean	Max	Min	Std Dev	Mean	Max	Min	Std Dev	Mean	Max	Min	Std Dev
Appeal_to_Authority	39	0.0348	0.1333	0.0000	0.0578	0.0972	0.5000	0.0000	0.1673	0.0214	0.0769	0.0000	0.0355
Appeal_to_fear-prejudice	63	0.1056	0.2024	0.0414	0.0380	0.0957	0.1818	0.0361	0.0351	0.1190	0.2282	0.0487	0.0429
Bandwagon	6	0.0257	0.2488	0.0000	0.0750	0.0622	0.7465	0.0000	0.1920	0.0166	0.1493	0.0000	0.0483
Black-and-White_Fallacy	43	0.1037	0.1387	0.0873	0.0142	0.1157	0.2484	0.0714	0.0443	0.1091	0.1250	0.0606	0.0275
Causal_Oversimplification	34	0.0854	0.2411	0.0136	0.0893	0.1315	0.2982	0.0244	0.1048	0.0686	0.2025	0.0094	0.0793
Doubt	108	0.1366	0.1802	0.0795	0.0344	0.1357	0.1866	0.0856	0.0364	0.1421	0.2006	0.0742	0.0407
Exaggeration,Minimisation	87	0.1456	0.2085	0.0834	0.0384	0.2027	0.2853	0.0902	0.0643	0.1161	0.1694	0.0653	0.0290
Flag-Waving	58	0.0958	0.1705	0.0385	0.0369	0.0799	0.1480	0.0301	0.0354	0.1224	0.2436	0.0531	0.0413
Loaded_Language	423	0.2651	0.2940	0.2418	0.0145	0.2486	0.2835	0.2263	0.0153	0.2847	0.3161	0.2554	0.0199
Name_Calling,Labeling	198	0.1838	0.2321	0.1365	0.0254	0.1966	0.2489	0.1547	0.0263	0.1731	0.2204	0.1221	0.0260
Obfuscation,Intentional_Vagueness,Confusion	2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Red_Herring	12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Reductio_ad_hitlerum	10	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Repetition	102	0.0190	0.0576	0.0000	0.0231	0.0151	0.0481	0.0000	0.0190	0.0261	0.0717	0.0000	0.0302
Slogans	26	0.0550	0.2288	0.0000	0.0917	0.1270	0.5196	0.0000	0.2127	0.0354	0.1584	0.0000	0.0594
Straw_Men	0	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Thought-terminating_Cliches	32	0.0079	0.0503	0.0000	0.0182	0.0158	0.1226	0.0000	0.0375	0.0053	0.0323	0.0000	0.0123
Whataboutism	12	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

Comparison with SOTA

original test set results

FLC Task: Test Set (Official Results)				
Rank	**Team**	**F_1**	**Precision**	**Recall**
1	**newspeak**	**0.2488**	0.2862	0.2200
2	Antiganda	0.2267	0.2882	0.1868
3	MIC-CIS	0.1998	0.2234	0.1808
4	Stalin	0.1453	0.1920	0.1169
5	CUNLP	0.1311	0.3234	0.0822
6	aschern	0.1090	0.0715	0.2294
7	ProperGander	0.0989	0.0651	0.2056
8	Sberiboba	0.0450	0.2974	0.0243
9	BananasInPajamas	0.0095	0.0095	0.0095
10	JUSTDeep	0.0011	0.0155	0.0006
11	Baseline	0.0000	0.0116	0.0000
12	MindCoders	0.0000	0.0000	0.0000
13	SU	0.0000	0.0000	0.0000

Table 6: Official test results for the FLC task.

Comparison with SOTA

results of retrained SOTA solution

Technique	Precision	Recall	F1 Score
OVERALL	**0.240388**	**0.220811**	**0.230184**
Appeal_to_Authority	0.086874	0.137800	0.106565
Appeal_to_fear-prejudice	0.157265	0.360784	0.219048
Bandwagon	0	0	0
Black-and-White_Fallacy	0.158259	0.326728	0.213233
Causal_Oversimplification	0.045226	0.321429	0.079295
Doubt	0.235908	0.489963	0.318476
Exaggeration, Minimisation	0.175325	0.286708	0.217591
Flag-Waving	0.352804	0.402321	0.375939
Loaded_Language	0.378651	0.371370	0.374975
Name_Calling, Labeling	0.346398	0.337607	0.341946
Obfuscation, Intentional_Vagueness, Confusion	0	0	0
Red_Herring	0	0	0
Reductio_ad_hitlerum	0.032821	0.098462	0.049231
Repetition	0.113971	0.019770	0.033696
Slogans	0.275086	0.317406	0.294735
Straw_Men	0	0	0
Thought-terminating_Cliches	0.585714	0.094470	0.162698
Whataboutism	0	0	0

10 best parameters
test set, unsloth-gemma-2-9b-bnb-4bit, 5 runs

			Overall F1				Binary F1				Number of failed chunks			
model_name	rank=α	epochs	mean	max	min	std	mean	max	min	std	mean	max	min	std
unsloth-gemma-2-9b-bnb-4bit	64	16	**0.1740**	**0.1792**	**0.1696**	0.0036	0.3002	0.3066	0.2942	0.0058	0.2	1	0	0.4472
	64	8	0.1678	0.1725	0.1606	0.0047	**0.3101**	**0.3155**	**0.3053**	0.0046	**0.0**	**0**	**0**	**0.0000**
	8	20	0.1645	0.1673	0.1605	**0.0030**	0.2915	0.2979	0.2839	0.0051	**0.0**	**0**	**0**	**0.0000**
	32	8	0.1620	0.1690	0.1524	0.0071	0.2977	0.3067	0.2898	0.0068	0.8	1	0	0.4472
	64	12	0.1602	0.1649	0.1563	0.0036	0.2858	0.2907	0.2829	**0.0030**	0.2	1	0	0.4472
	16	20	0.1589	0.1638	0.1518	0.0046	0.2931	0.2974	0.2902	0.0028	**0.0**	**0**	**0**	**0.0000**
	64	20	0.1585	0.1637	0.1531	0.0044	0.2833	0.2939	0.2782	0.0061	0.2	1	0	0.4472
	32	12	0.1462	0.1516	0.1387	0.0049	0.2903	0.3019	0.2832	0.0082	0.2	1	0	0.4472
	32	16	0.1442	0.1486	0.1386	0.0039	0.2776	0.2800	0.2756	**0.0019**	**0.0**	**0**	**0**	**0.0000**
	4	20	0.1331	0.1362	0.1275	0.0037	0.2778	0.2833	0.2633	0.0085	0.6	2	0	0.8944

Rescaled results

$$\frac{0.2488}{0.2302} \times 0.1740 = 0.1881$$

Rank	Team	F1 Score
1	newspeak	0.2488
2	Antiganda	0.2267
3	MIC-CIS	0.1998
4	**OUR_MODEL**	**0.1881**
5	Stalin	0.1453
6	CUNLP	0.1311
7	aschern	0.1090
8	ProperGander	0.0989
9	Sberiboba	0.0450
10	BananasInPajamas	0.0095
11	JUSTDeep	0.0011
12	Baseline	0.0000
13	MindCoders	0.0000
14	SU	0.0000

Gathered datasets

News Dataset

Basic statistics

Domain	Number of Articles	Number of Techniques	Techniques per Article
wydarzenia.interia.pl	403	3,870	9.6030
wiadomosci.onet.pl	79	1,334	15.5116
TOTAL	**489**	**5204**	**10.6421**

News Dataset Detailed statistics

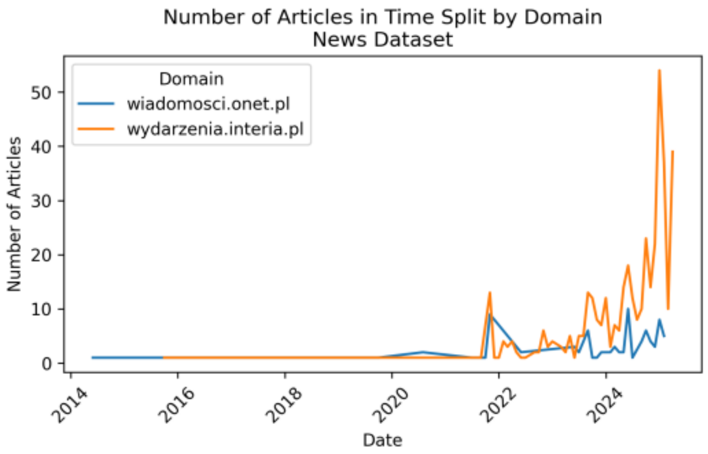
Metric	Statistic	wiadomosci.onet.pl	wydarzenia.interia.pl	TOTAL
Articles	unique count	86	403	489
Articles with No Prediction*	unique count	7	12	19
Number of Failed Chunks	sum	0	4	4
Number of Articles with Failed Chunks	count	0	4	4
Length of Translated Text (number of chars.)	mean	8,972.4989	5,998.5044	6,762.0745
	min	82	756	82
	max	28,324	20,784	28,324
	std	5,098.1658	4,119.1925	4,579.0979
Number of Words Translated Text	mean	1,472.4430	975.2916	1102.9347
	min	14	115	14
	max	4,887	3,523	4,887
	std	870.0814	687.3889	769.8062
Number of Words In Propaganda Technique Excerpt	mean	6.0440	6.4784	6.3668
	min**	0	0	0
	max	65	89	89
	std	7.8270	7.9649	7.9312
Number of Characters In Propaganda Technique Excerpt	mean	36.6719	39.3797	38.6845
	min**	0	0	0
	max	416	551	551
	std	46.2031	46.6468	46.5439

*Articles with no prediction refer to articles where no propaganda techniques were identified or all chunks had failed during inference.

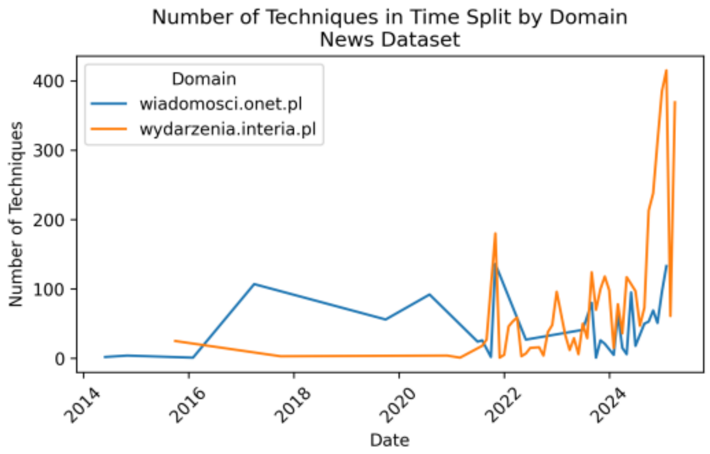
**The minimum value of 0 indicates articles without any propaganda technique excerpts.

News Dataset

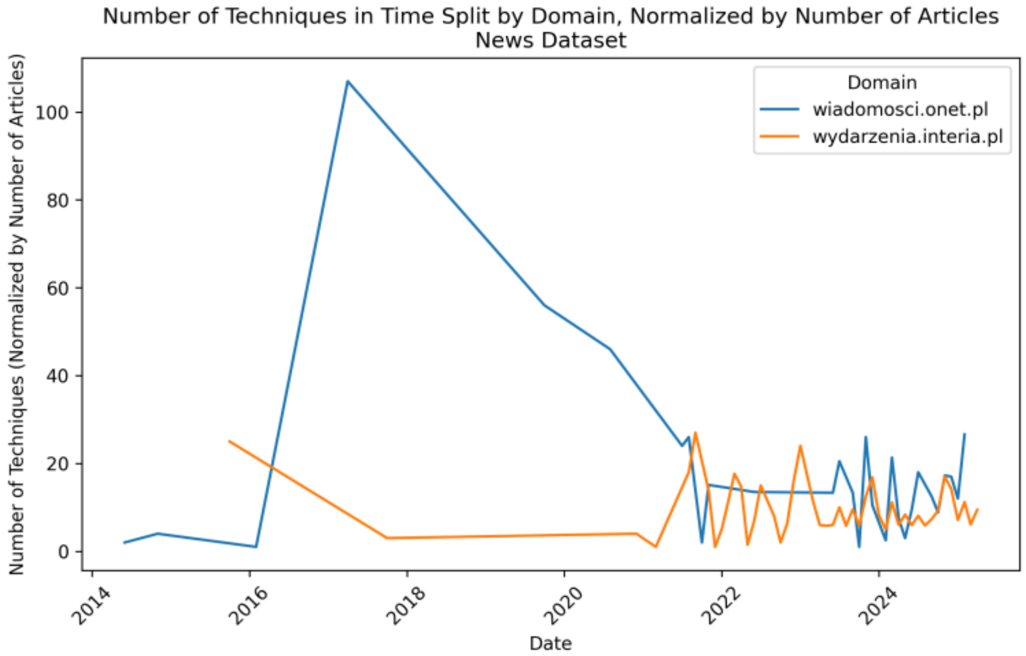
Temporal analysis



(a) Number of news articles over time



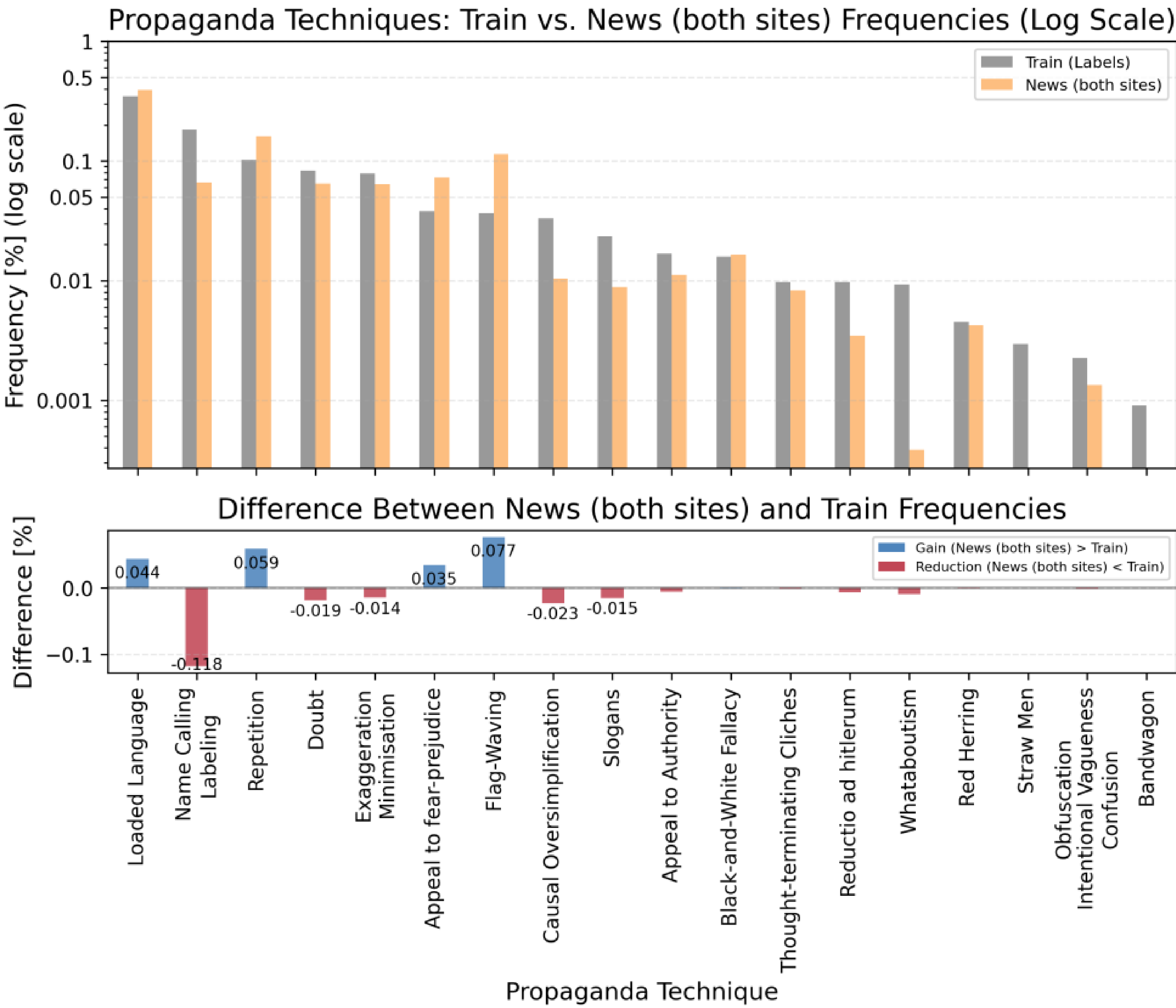
(b) Number of propaganda techniques over time



(c) Number of propaganda techniques normalized by number of articles

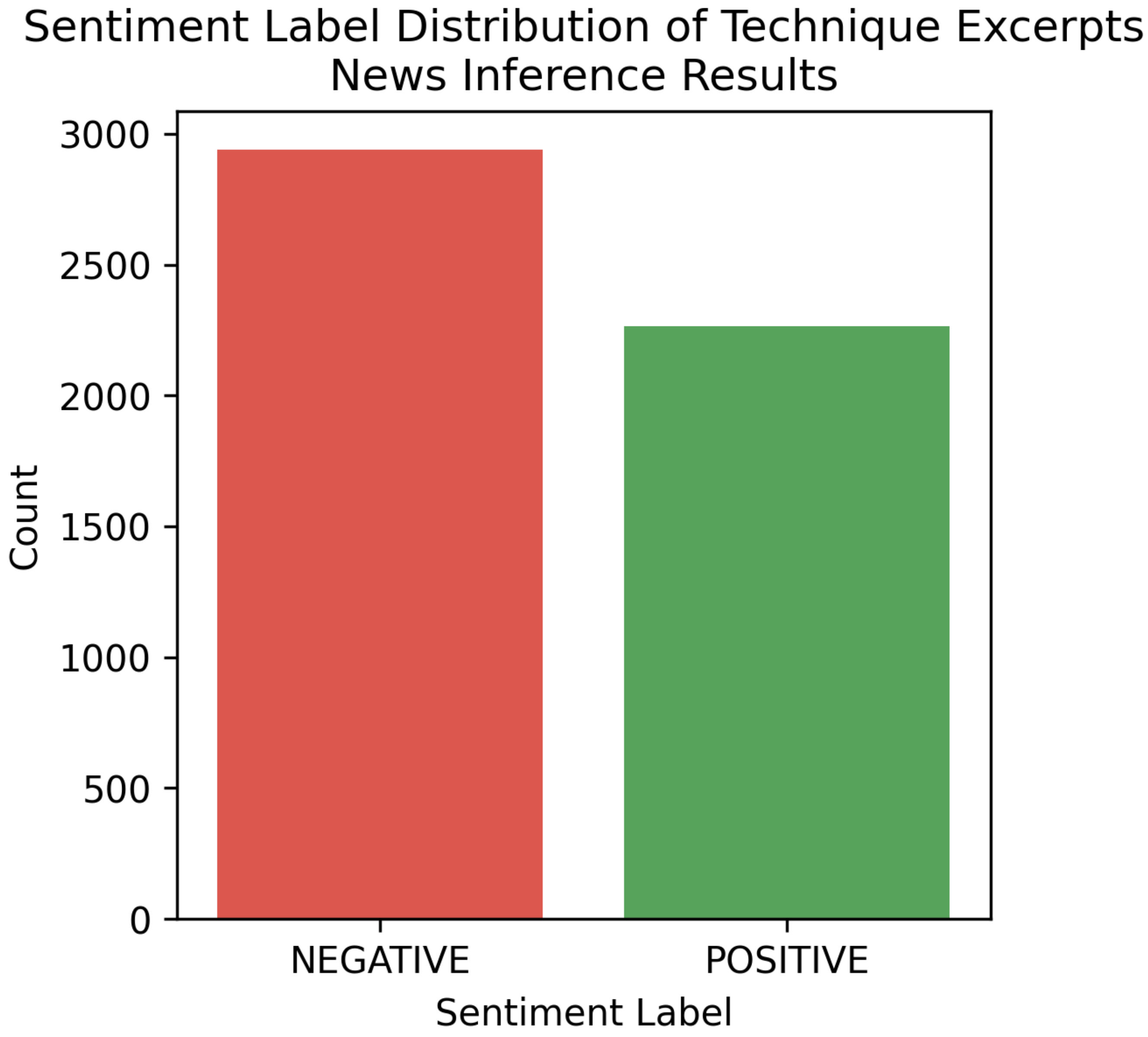
News Dataset

Comparison with train data



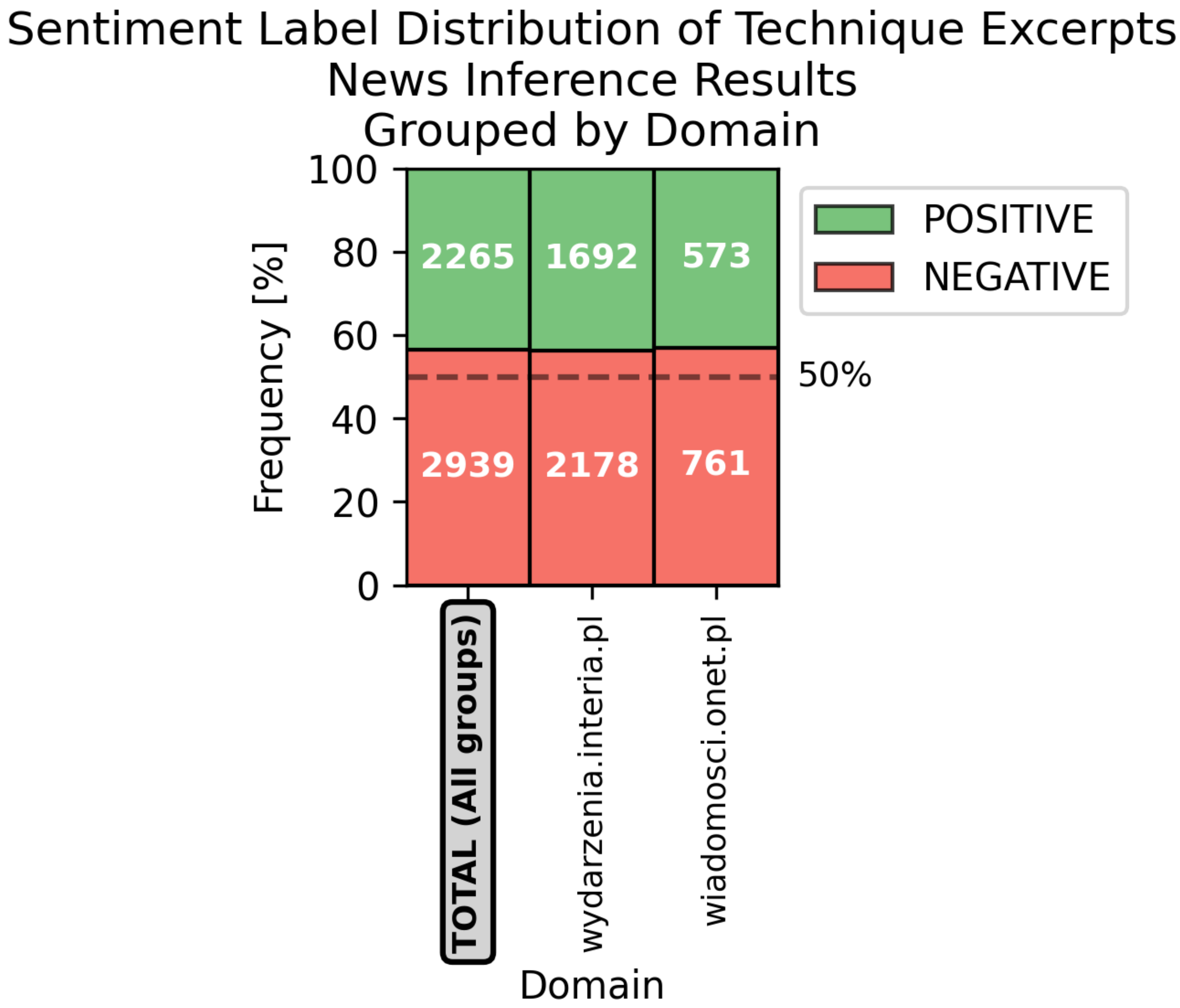
News dataset

Sentiment overall



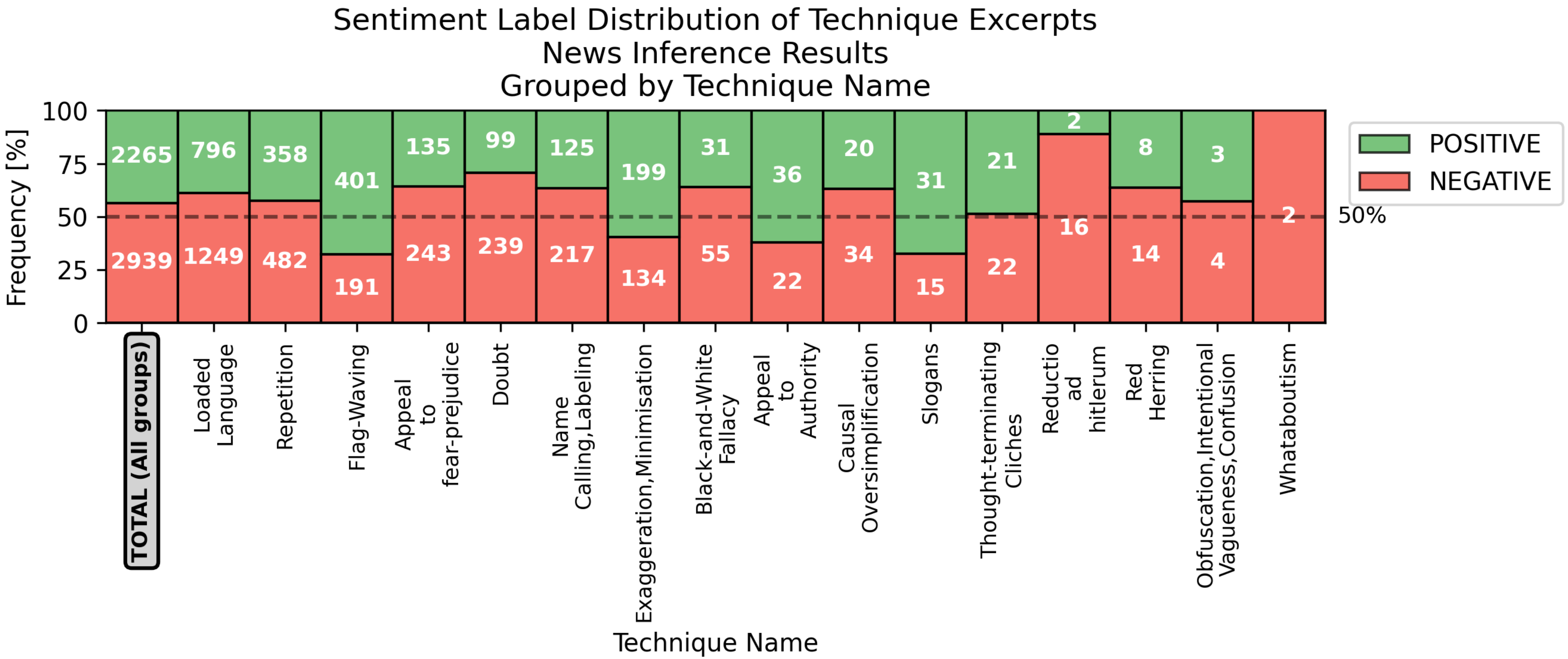
News dataset

Sentiment by domain

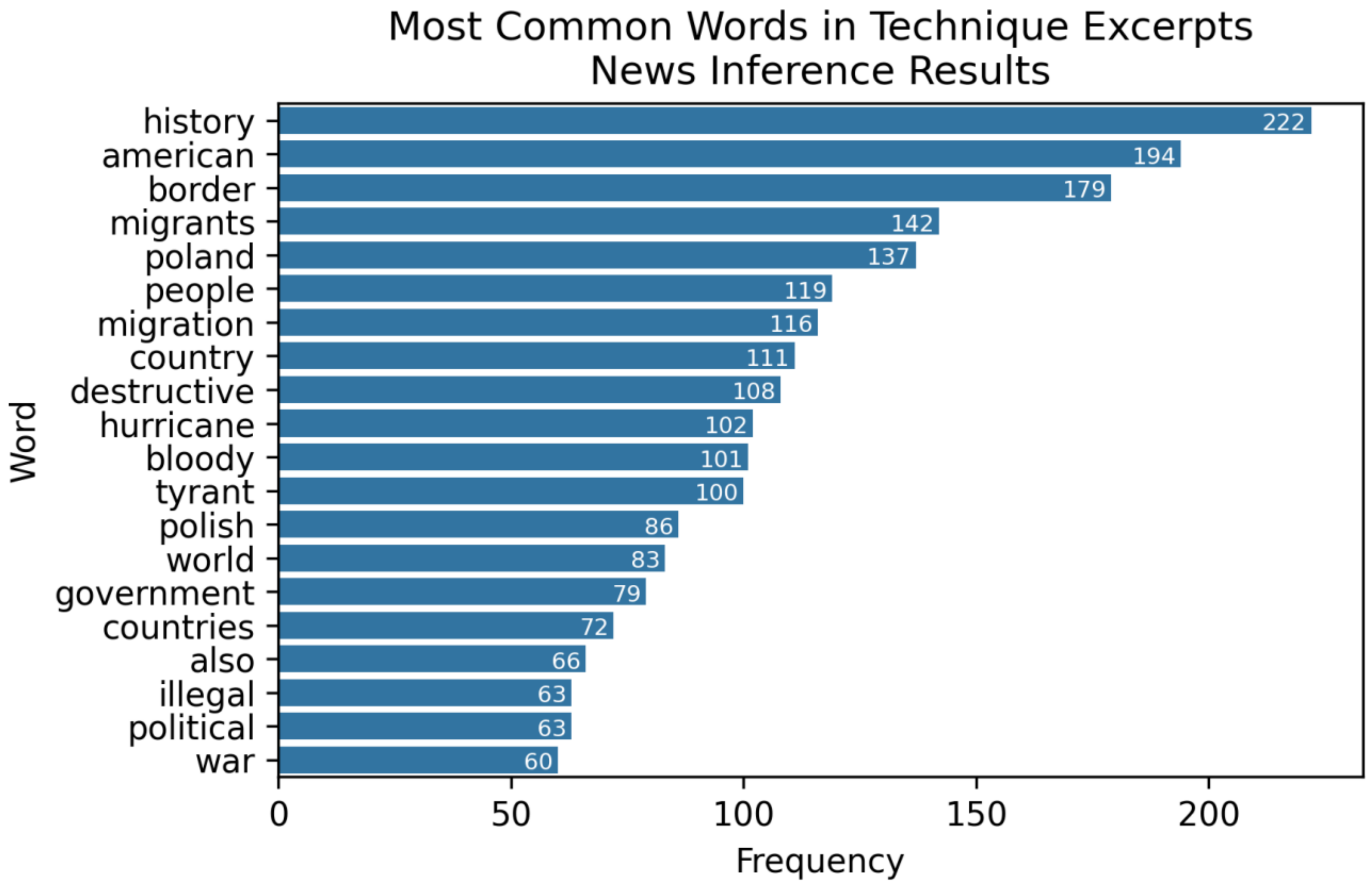


News dataset

Sentiment by technique

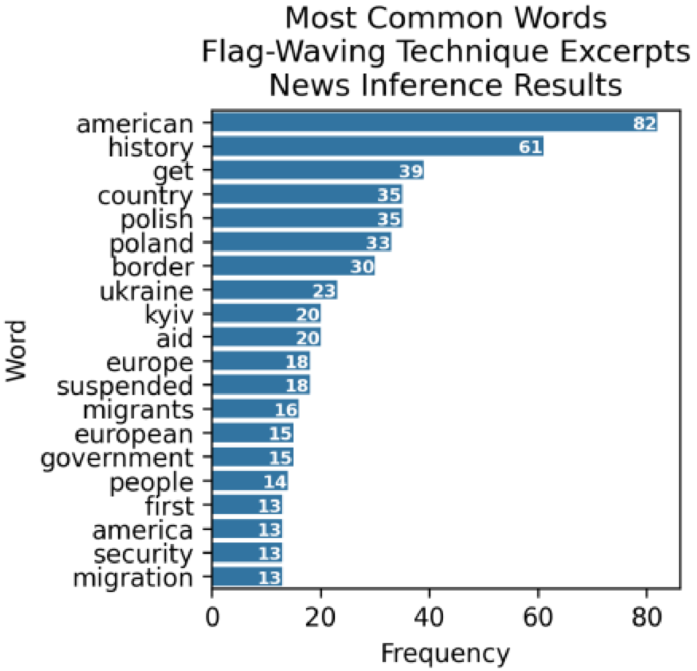


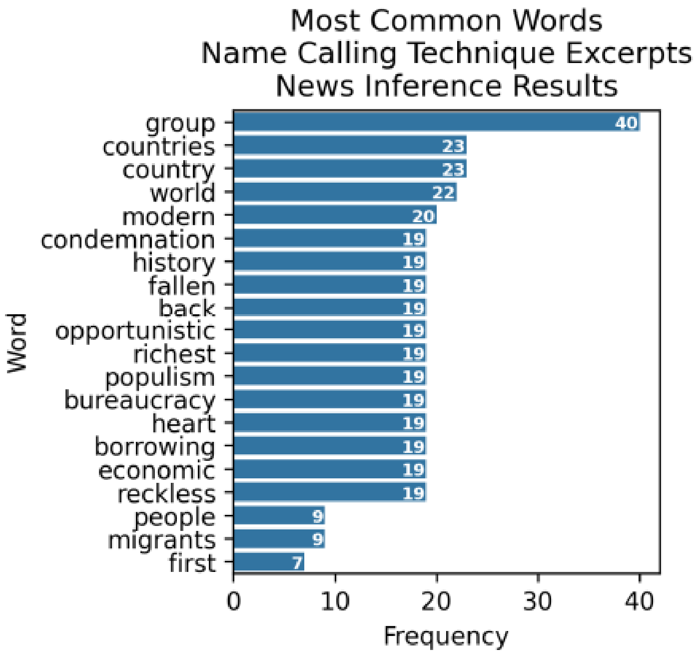
News dataset
most common words



News dataset

Flag Waving and Name Calling





TikTok Dataset
Basic statistics

Political Club	Number of Videos	Number of Techniques	Number of People	Techniques per Video	Videos per Person
PiS	604	4898	8	8.1093	75.5000
PO-KO	70	301	12	4.3000	5.8333
Konfederacja	66	345	1	5.2273	66.0000
Lewica	46	311	5	6.7609	9.2000
Polska2050-TD	36	175	1	4.8611	36.0000
Razem	5	43	1	8.6000	5.0000
niez.	1	1	1	1.0000	1.0000
TOTAL	**828**	**6074**	**29***	**7.3358**	**28.5517**

*29 total politicians as **Adrian Zandberg** (username: **adrian.zandberg**) appeared in two clubs: **Razem** and **Lewica**.

TikTok Dataset

Detailed statistics

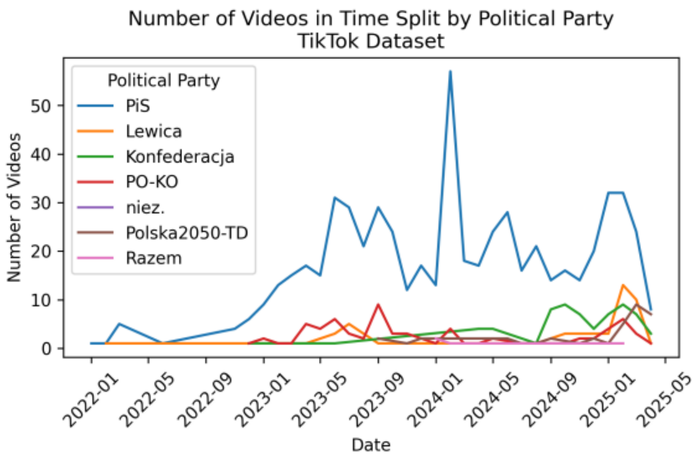
Metric	Statistic	TOTAL
Videos	unique count	828
Videos with No Prediction*	unique count	4
Number of Failed Chunks	sum	5
Number of Videos with Failed Chunks	nunique	5
Length of Translated Text (number of chars.)	mean	3,840.6326
	min	104
	max	23,308
	std	4,612.2207
Number of Words Translated Text	mean	647.9582
	min	18
	max	3,863
	std	768.5064
Number of Words In Propaganda Technique Excerpt	mean	8.8868
	min**	0
	max	96
	std	10.7224
Number of Characters In Propaganda Technique Excerpt	mean	51.5814
	min**	0
	max	564
	std	62.1248

*Articles with no prediction refer to articles where no propaganda techniques were identified or all chunks had failed during inference.

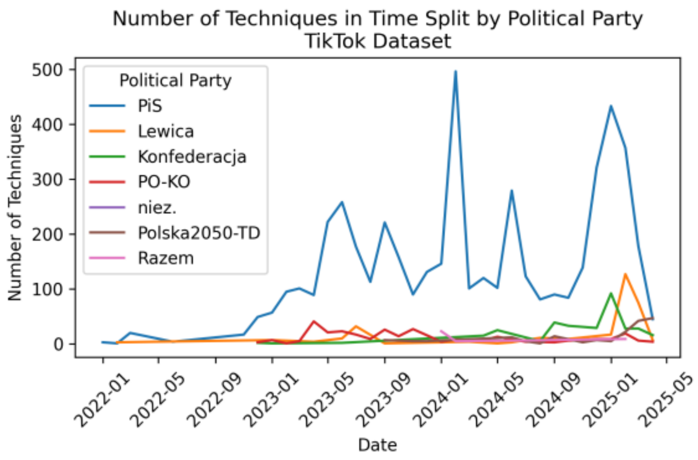
**The minimum value of 0 indicates articles without any propaganda technique excerpts.

TikTok Dataset

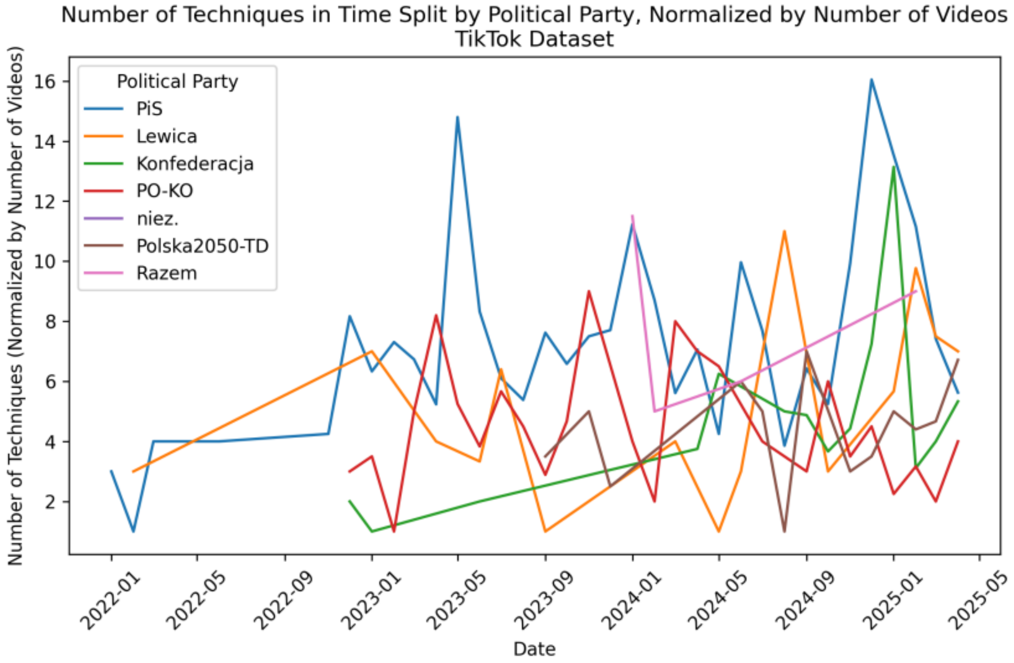
Temporal analysis



(a) Number of TikTok videos over time



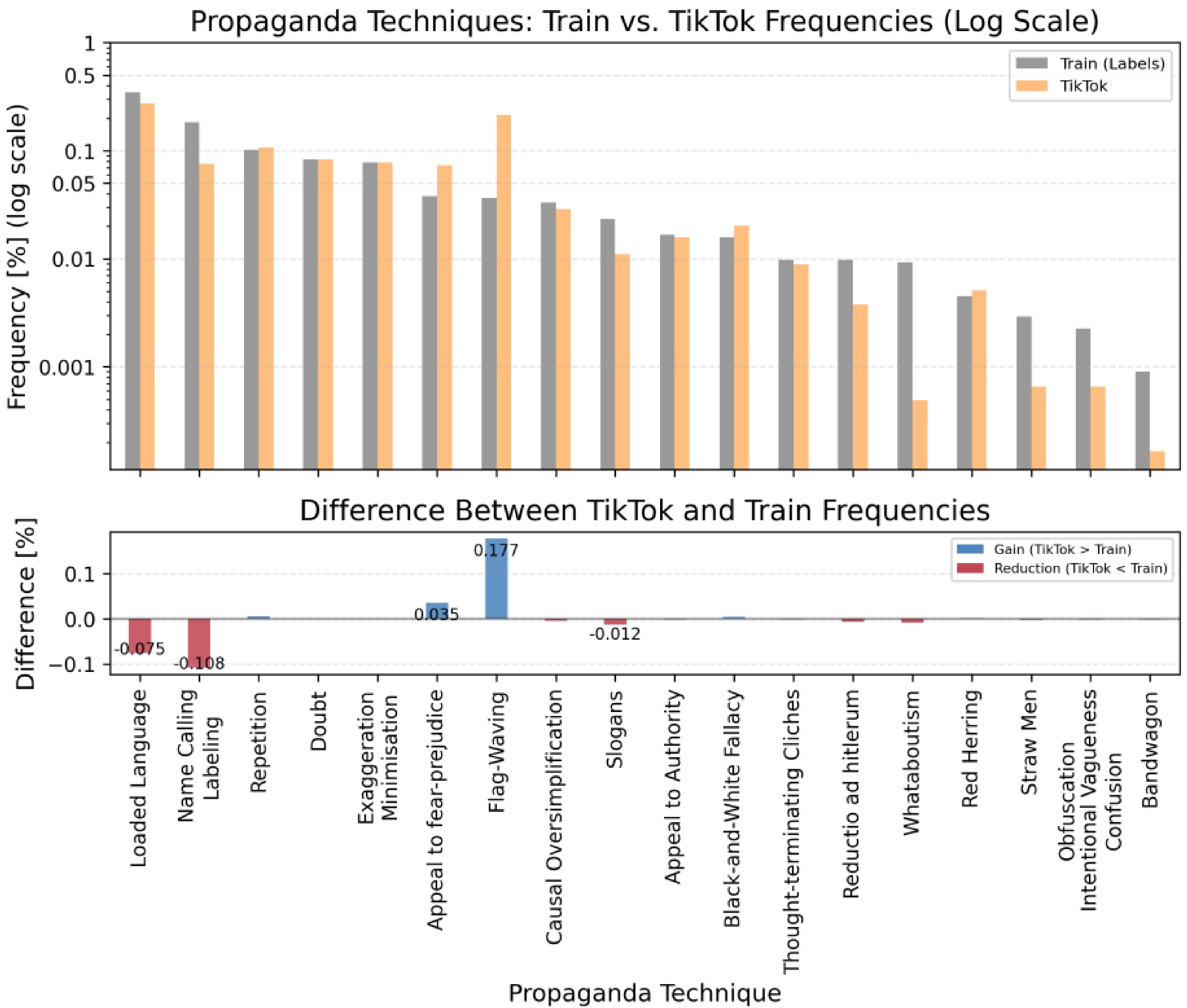
(b) Number of propaganda techniques over time



(c) Number of propaganda techniques normalized by number of TikTok videos

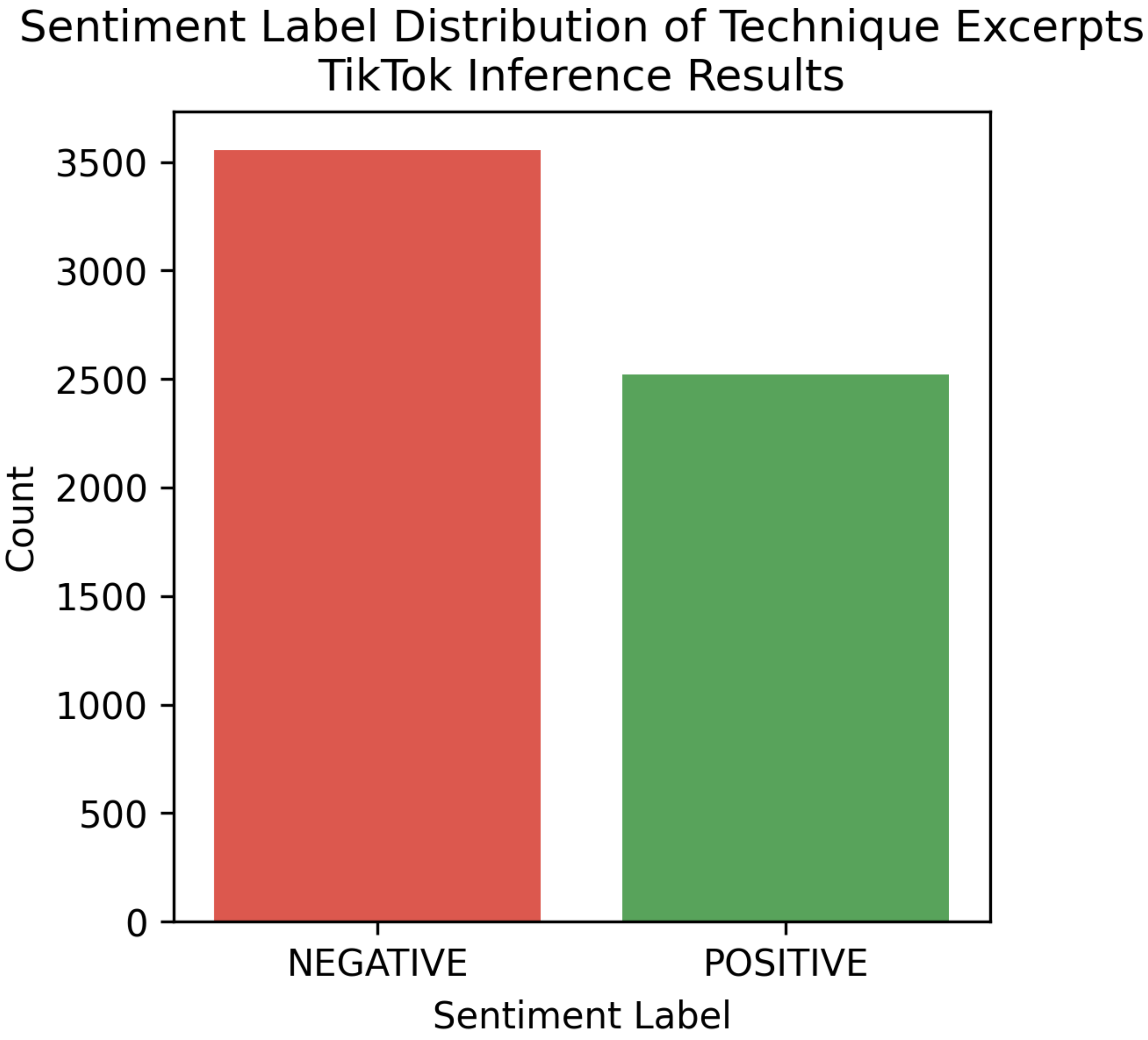
TikTok Dataset

Comparison with train data

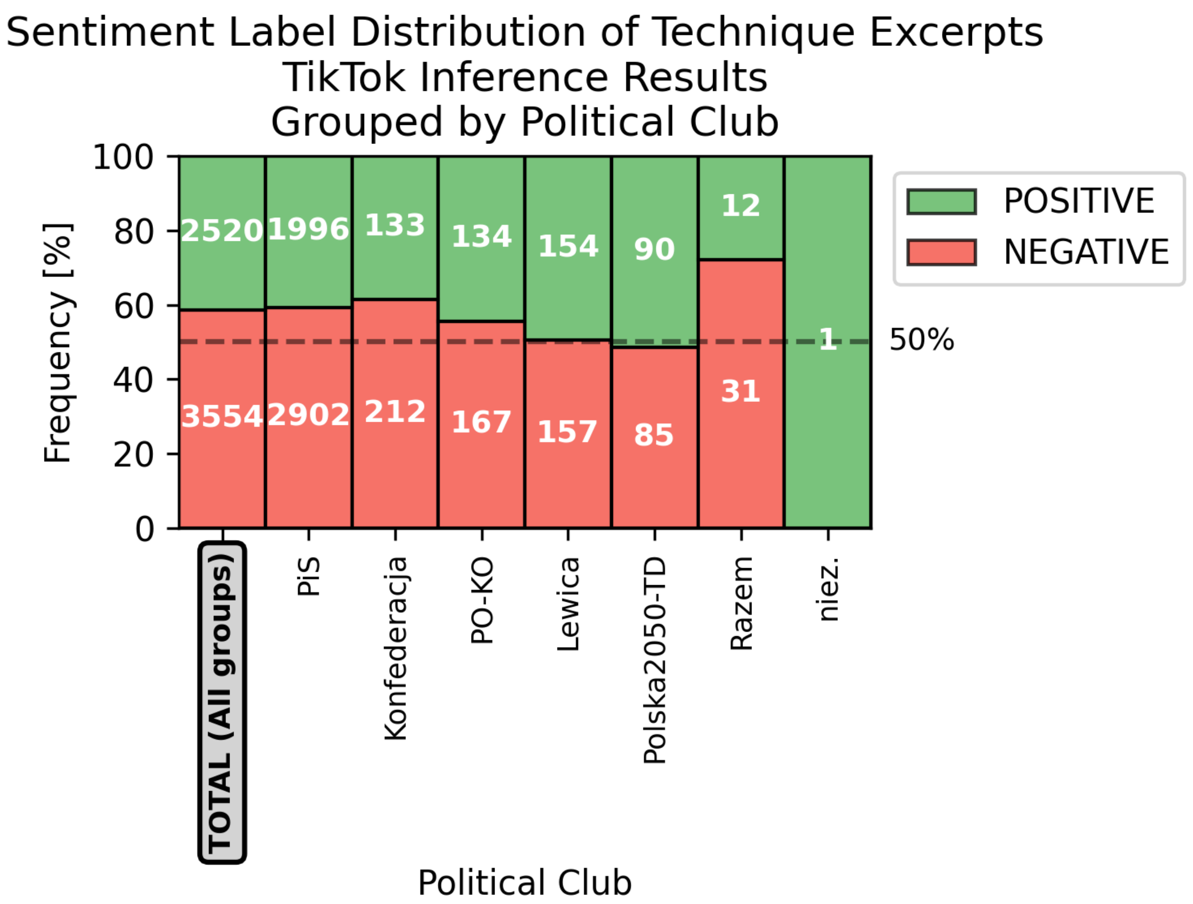


TikTok dataset

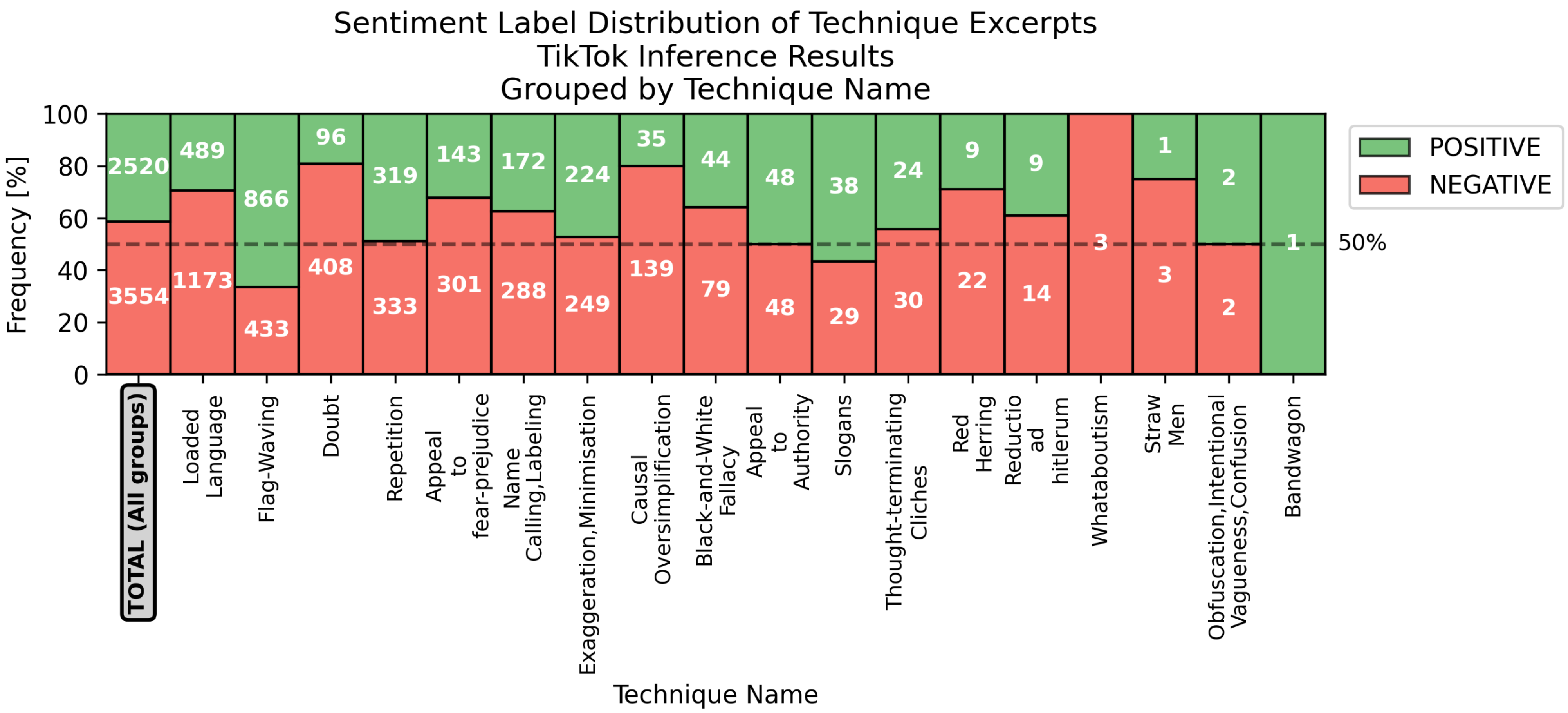
Sentiment overall



TikTok dataset
Sentiment by club

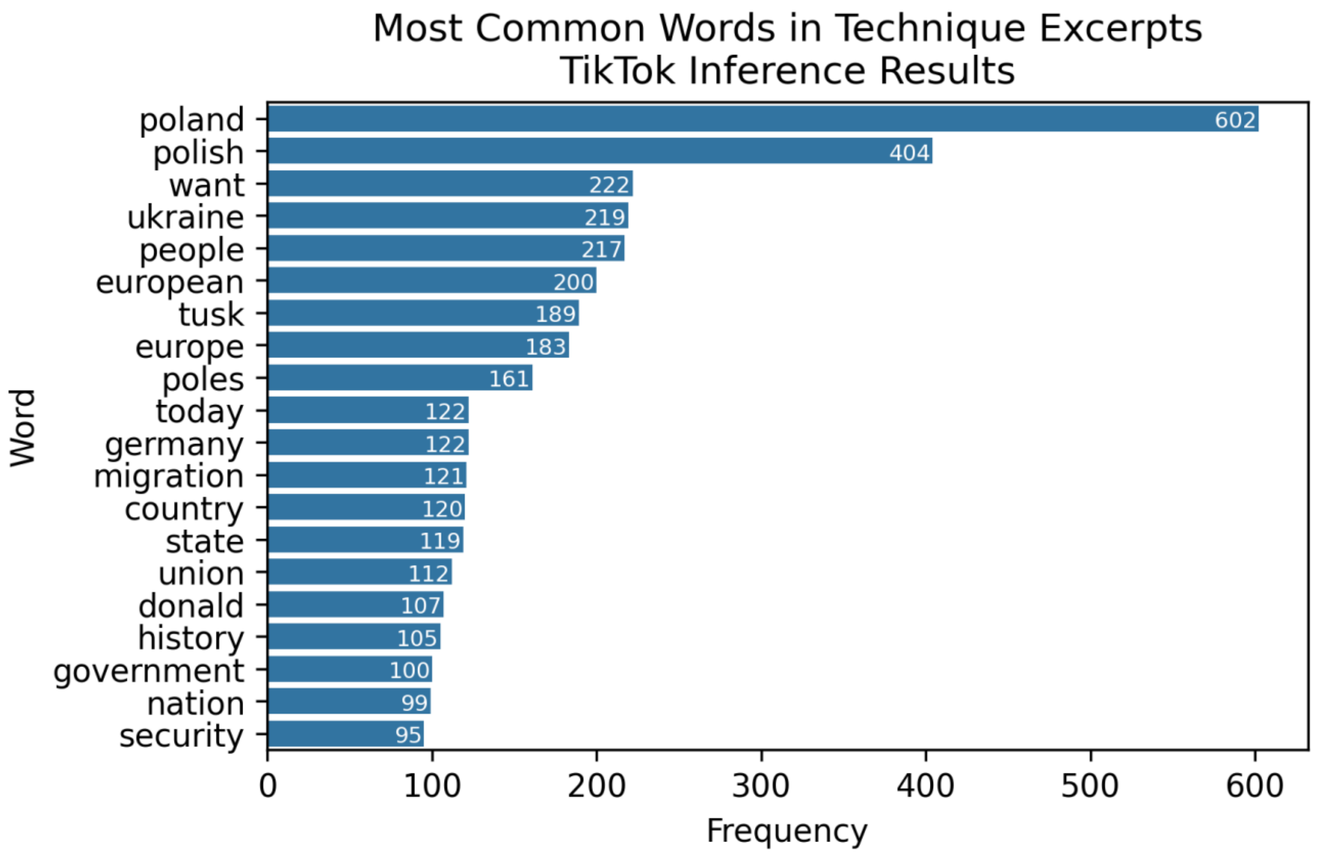


TikTok dataset
Sentiment by technique



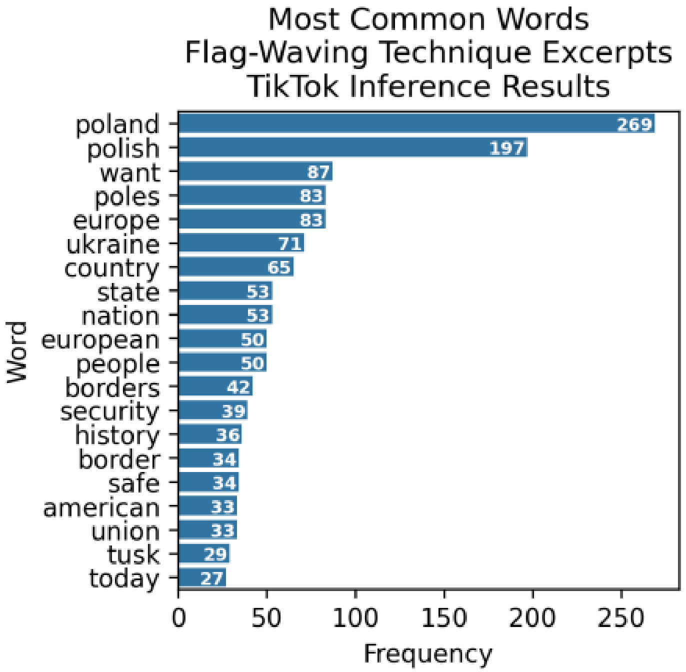
TikTok dataset

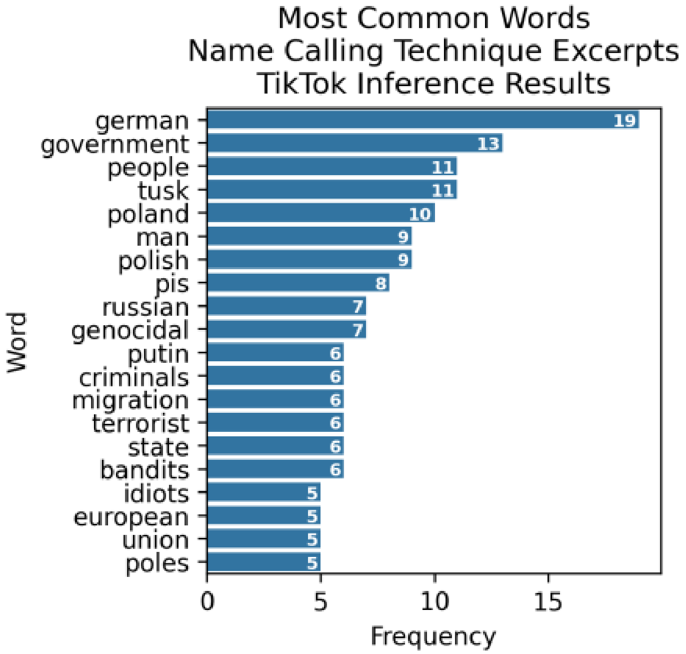
most common words



TikTok dataset

Flag Waving and Name Calling





Sejm Dataset
Basic statistics

Political Club	Number of Speeches	Number of Techniques	Number of People	Techniques per Speech	Speeches per Person
PiS	2479	35622	292	14.3695	8.4897
PO-KO	1584	18782	207	11.8573	7.6522
other or missing*	1034	22724	192	21.9768	5.3854
Konfederacja	632	6481	23	10.2547	27.4783
Lewica	620	5331	43	8.5984	14.4186
KP	233	2360	26	10.1288	8.9615
PSL-KP	156	2581	17	16.5449	9.1765
PSL-TD	149	2149	23	14.4228	6.4783
Kukiz15	140	1576	17	11.2571	8.2353
Polska2050	124	1043	6	8.4113	20.6667
Polska2050-TD	117	1350	28	11.5385	4.1786
niez.**	87	1181	18	13.5747	4.8333
Republikanie	43	417	3	9.6977	14.3333
LD	41	292	3	7.1220	13.6667
Razem	33	517	5	15.6667	6.6000
UPR	30	470	4	15.6667	7.5000
TERAZ!	16	574	2	35.8750	8.0000
PP	13	180	2	13.8462	6.5000
PS	10	97	3	9.7000	3.3333
WiS	4	22	1	5.5000	4.0000
PSL-UED	2	15	1	7.5000	2.0000
TOTAL	**7547**	**103764**	**916*****	**13.7490**	**8.2391**

*This class includes non-MPs, not associated with any party/club, like the President, etc.

***niez.* stands for *niezrzeszony*, meaning non-affiliated (independent) MP.

***The total number of politicians may include some individuals who appeared in multiple political clubs.

Sejm Dataset

Detailed statistics

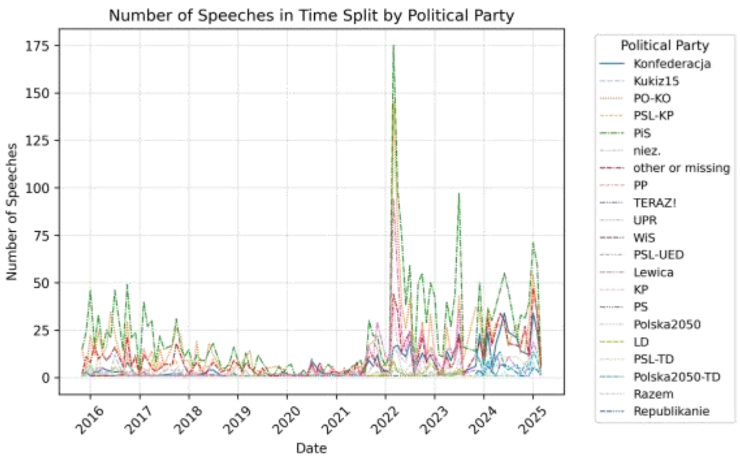
Metric	Statistic	TOTAL
Articles	unique count	7,547
Articles with No Prediction*	unique count	129
Number of Failed Chunks	sum	132
Number of Articles with Failed Chunks	nunique	132
Length of Translated Text (number of chars.)	mean	9,804.5252
	min	103
	max	86,939
	std	14,093.5213
Number of Words Translated Text	mean	1,594.1291
	min	18
	max	14,448
	std	2,276.8124
Number of Words In Propaganda Technique Excerpt	mean	8.3222
	min**	0
	max	221
	std	10.9544
Number of Characters In Propaganda Technique Excerpt	mean	49.8133
	min**	0
	max	1,502
	std	65.9154

*Articles with no prediction refer to articles where no propaganda techniques were identified or all chunks had failed during inference.

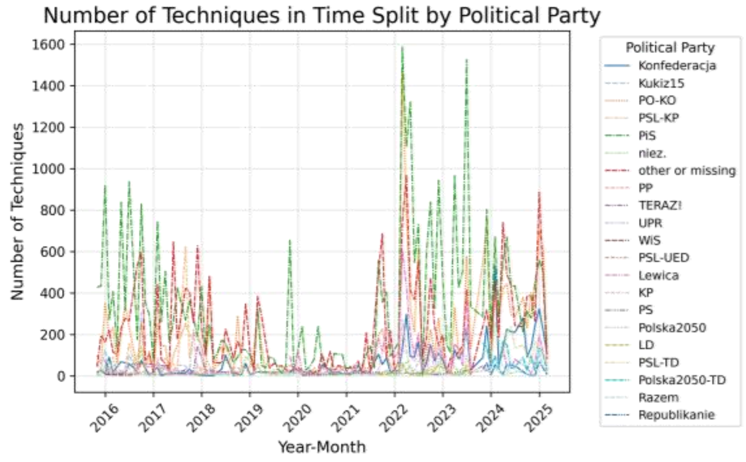
**The minimum value of 0 indicates articles without any propaganda technique excerpts.

Sejm Dataset

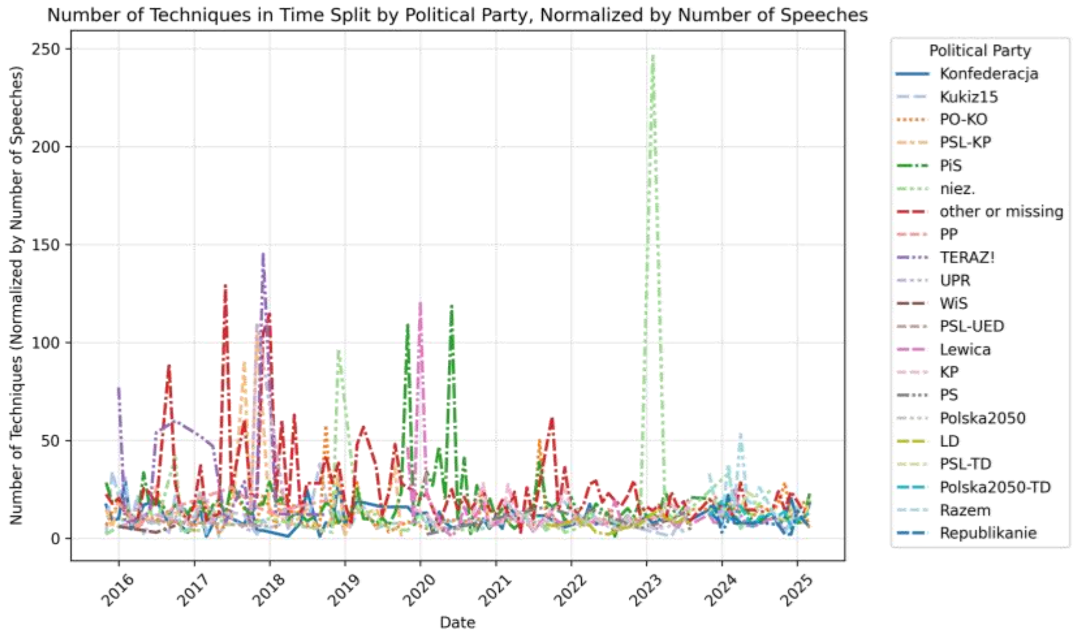
Temporal analysis



(a) Number of Sejm speeches over time



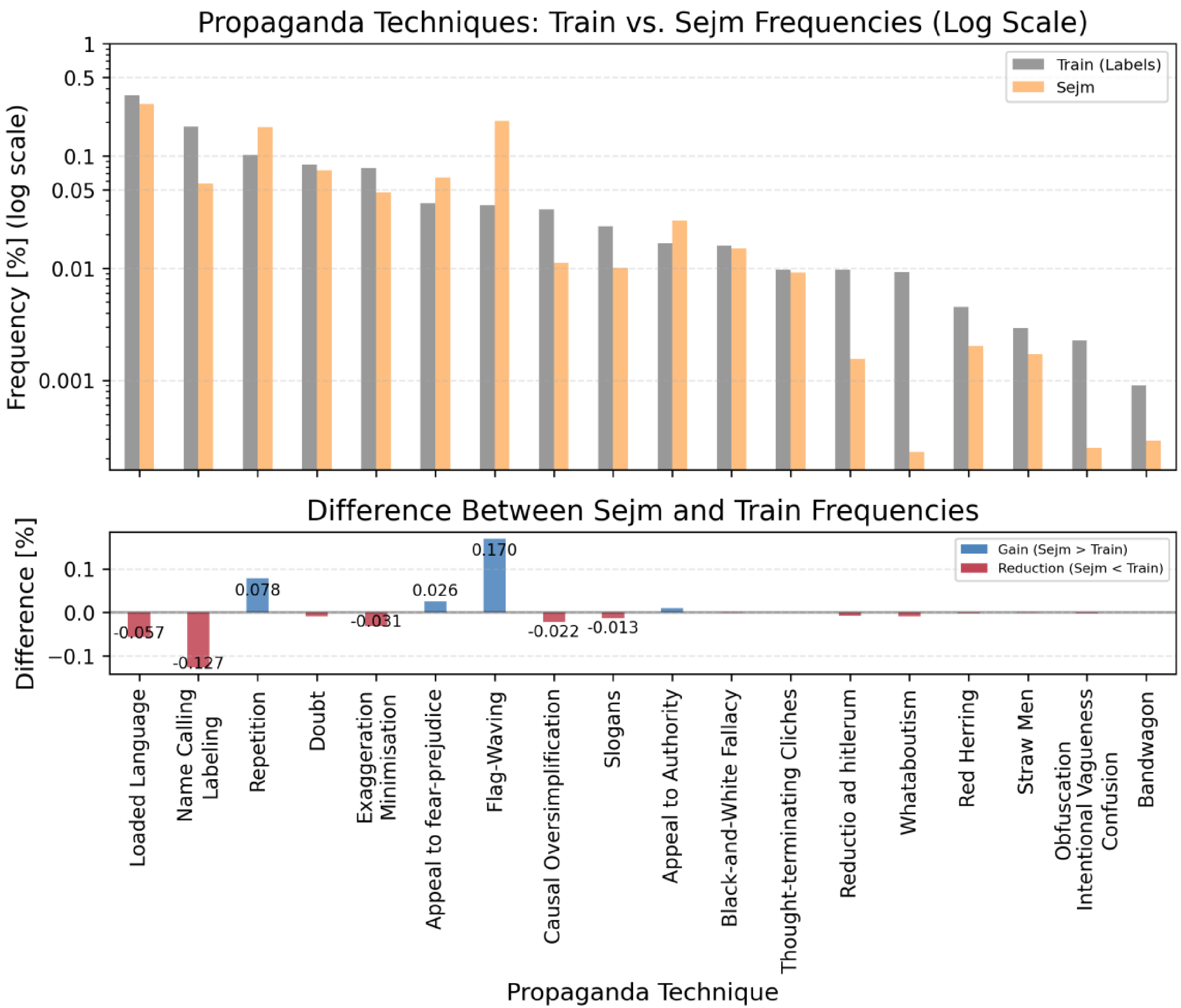
(b) Number of propaganda techniques over time



(c) Number of propaganda techniques normalized by number of Sejm speeches

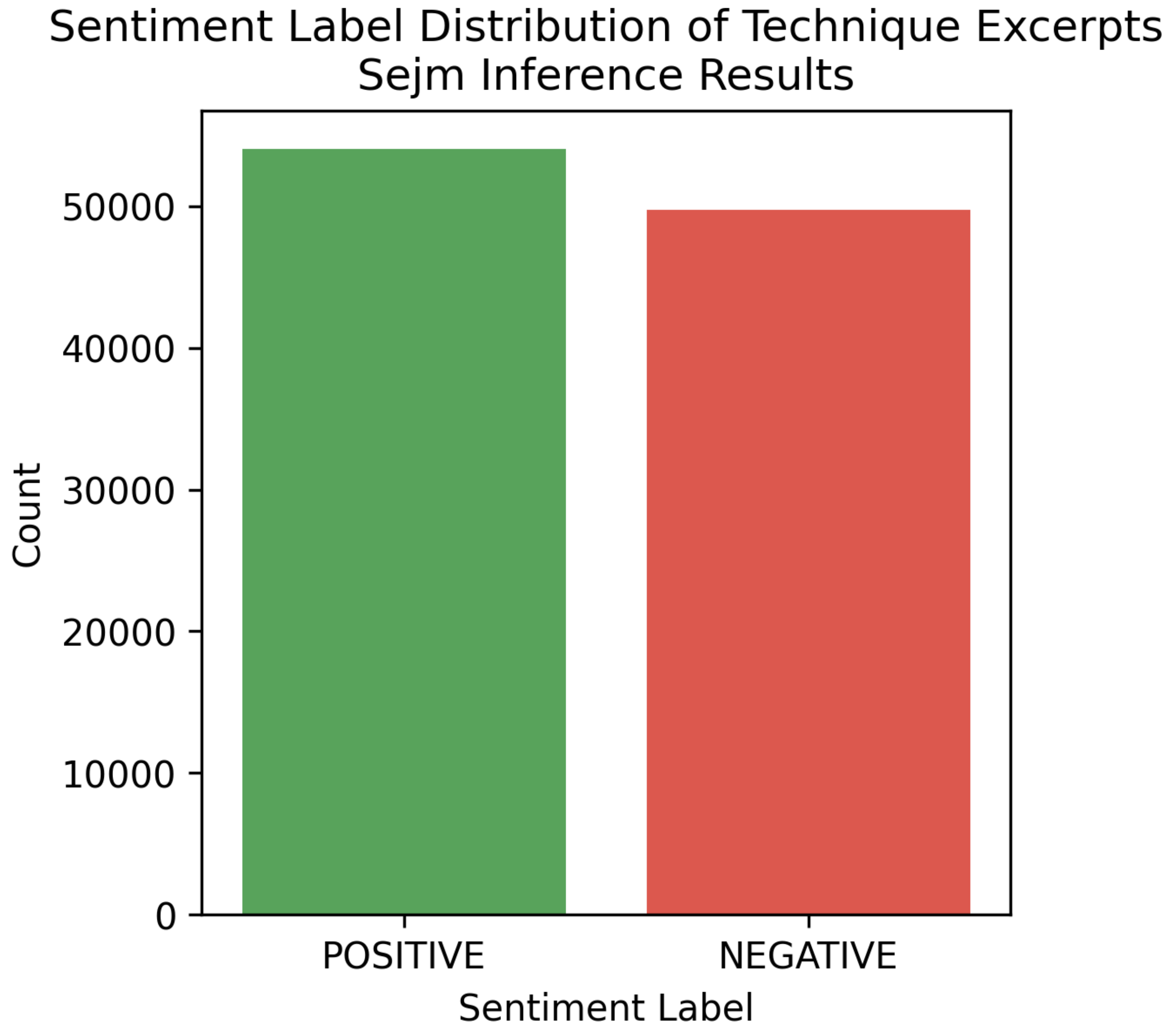
Sejm Dataset

Comparison with train data

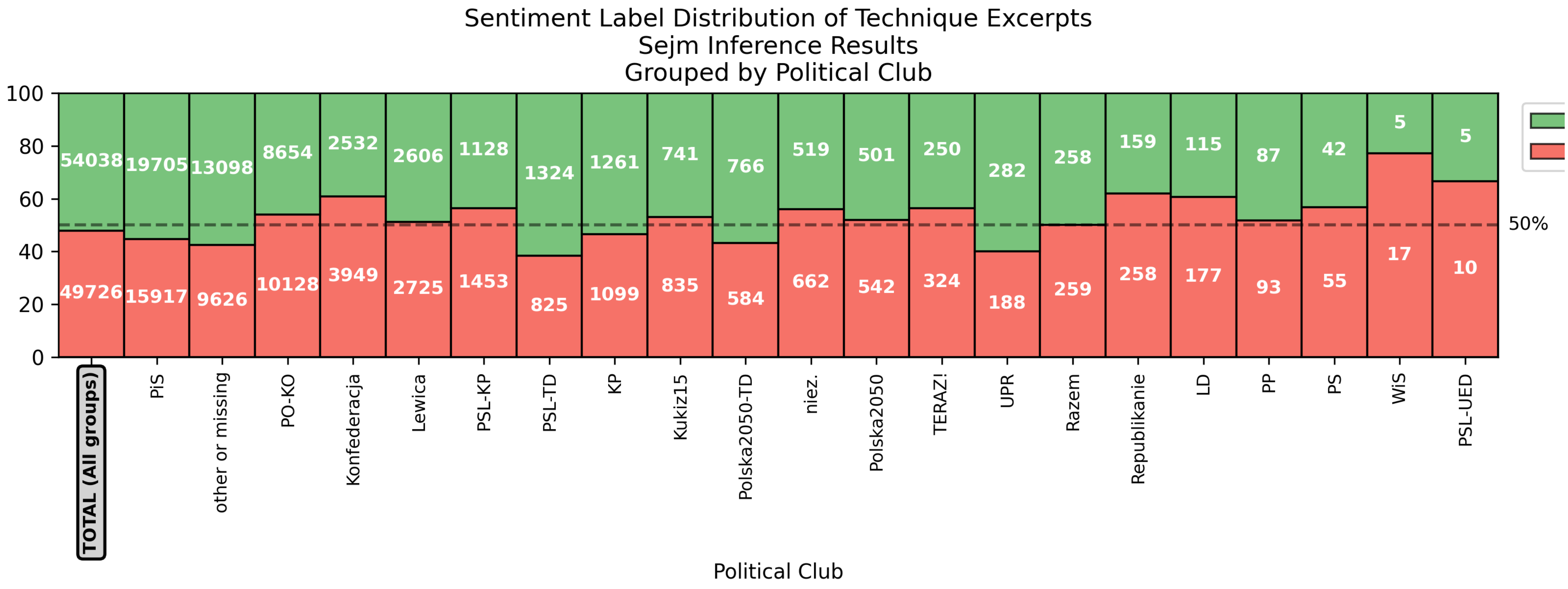


Sejm dataset

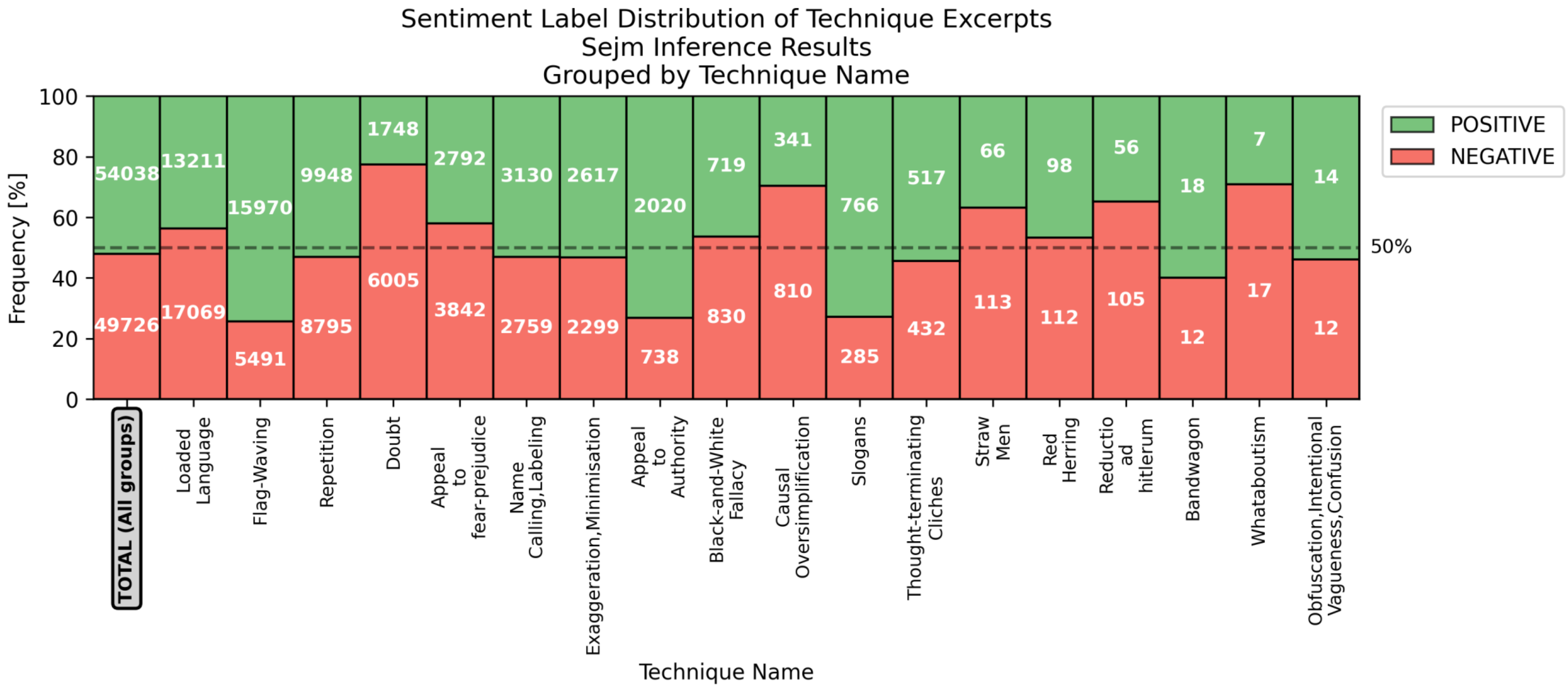
Sentiment overall



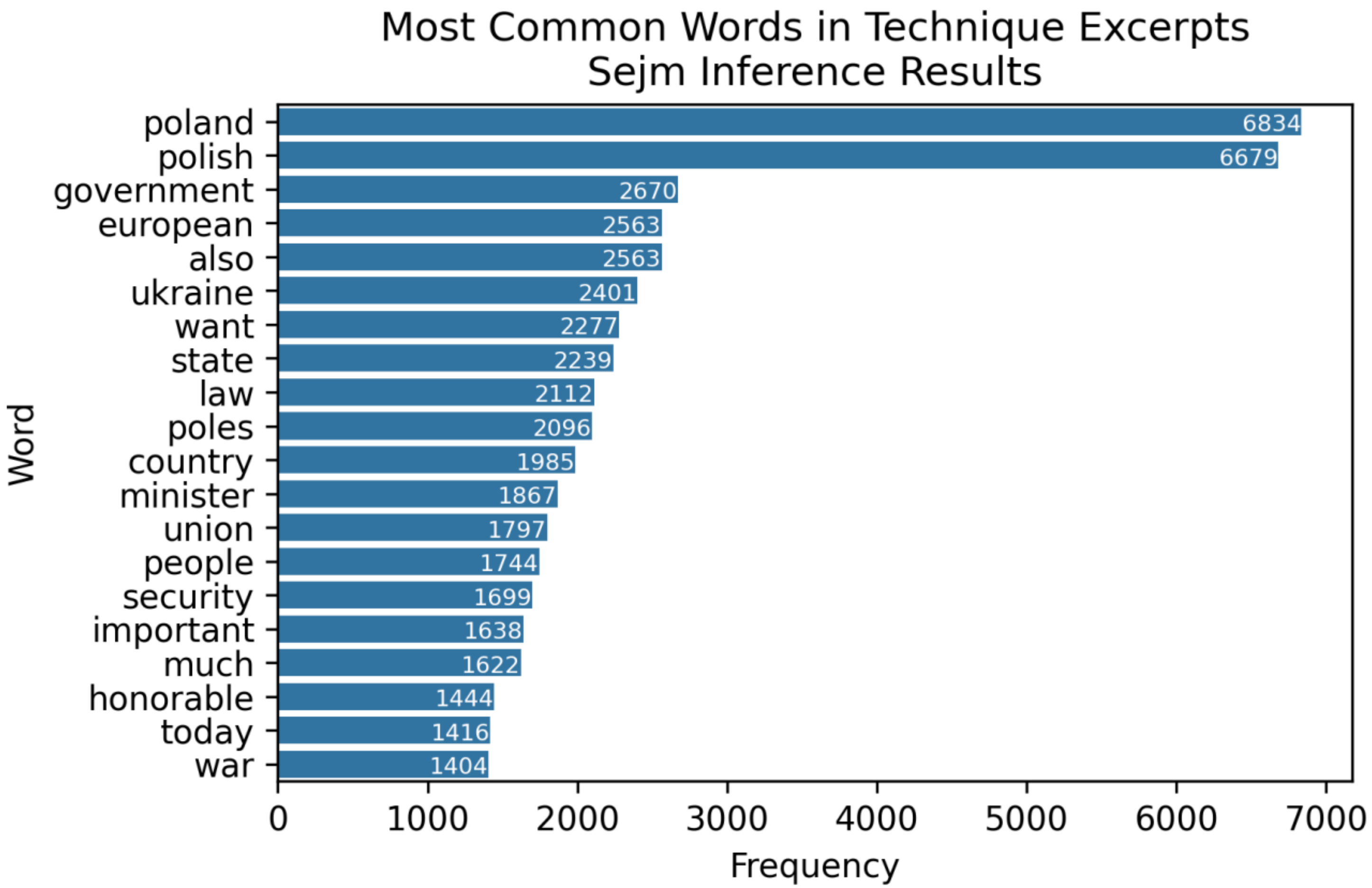
Sejm dataset
Sentiment by club



Sejm dataset
Sentiment by technique

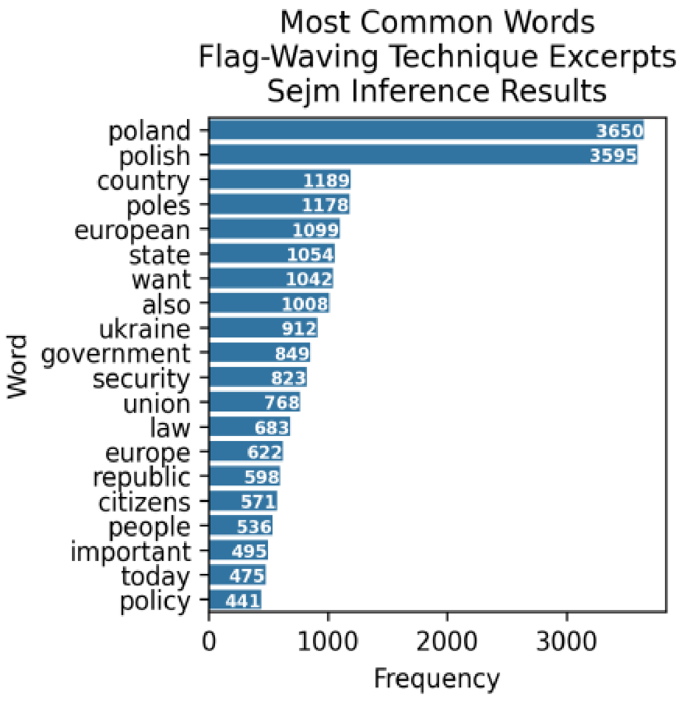


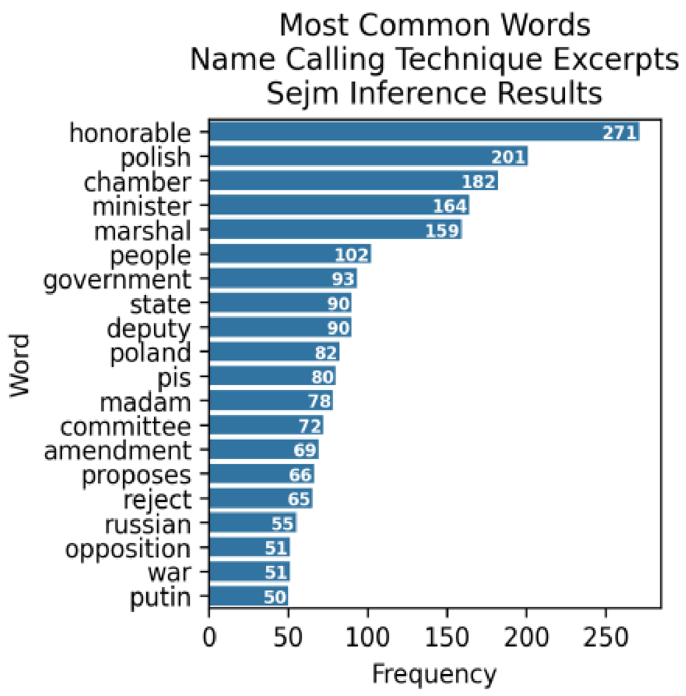
Sejm dataset most common words



Sejm dataset

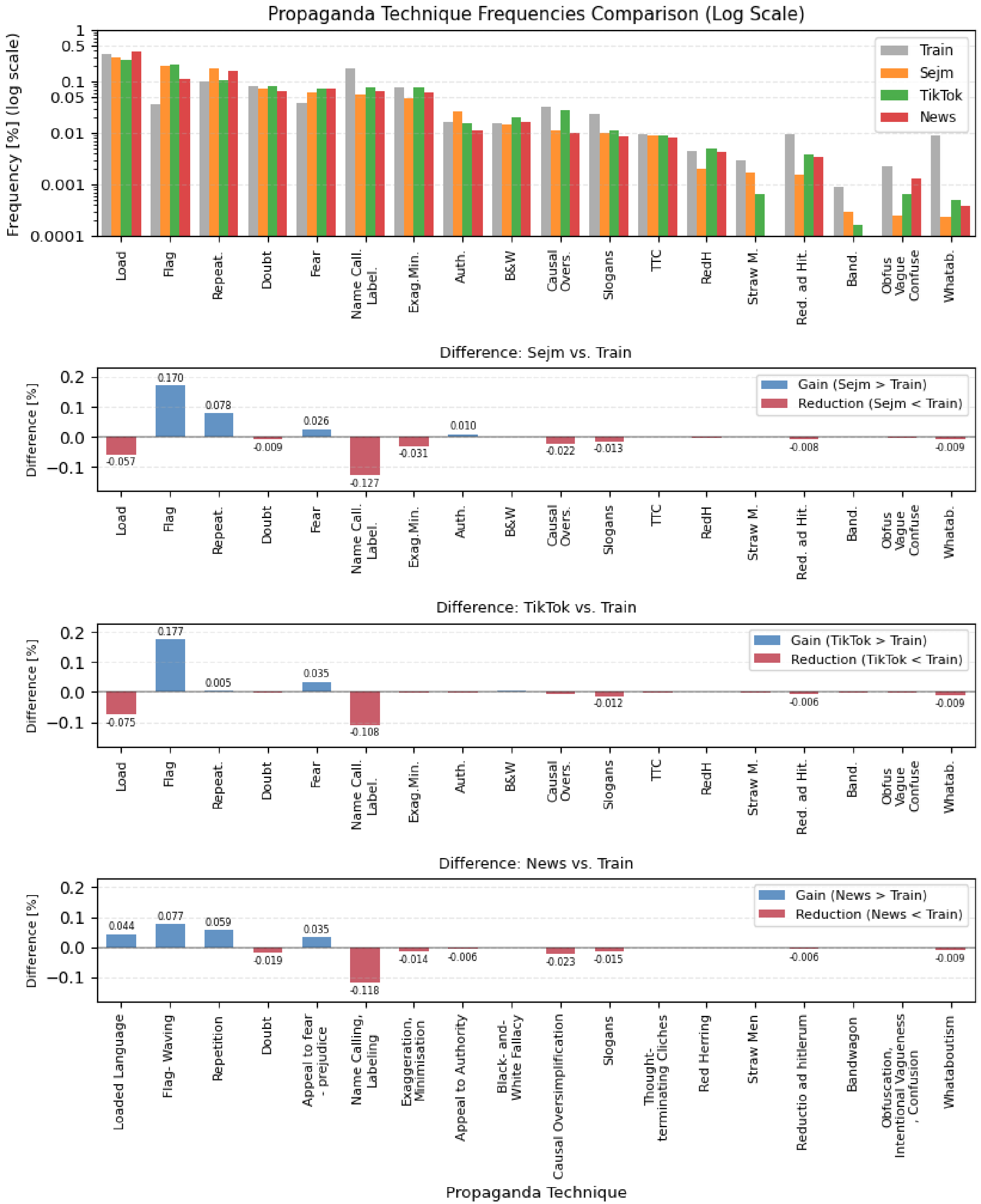
Flag Waving and Name Calling





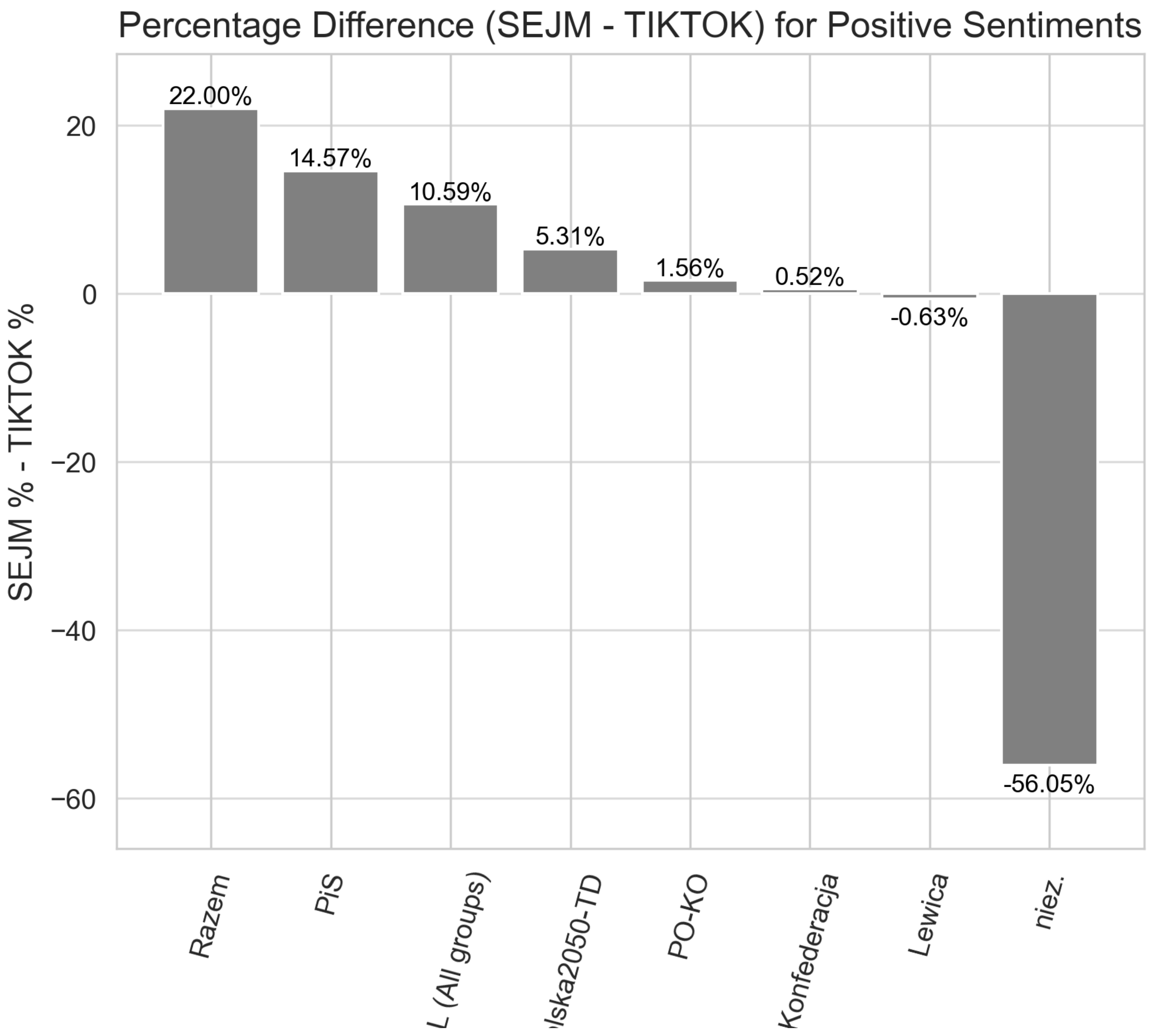
Comparison of all datasets

technique frequencies

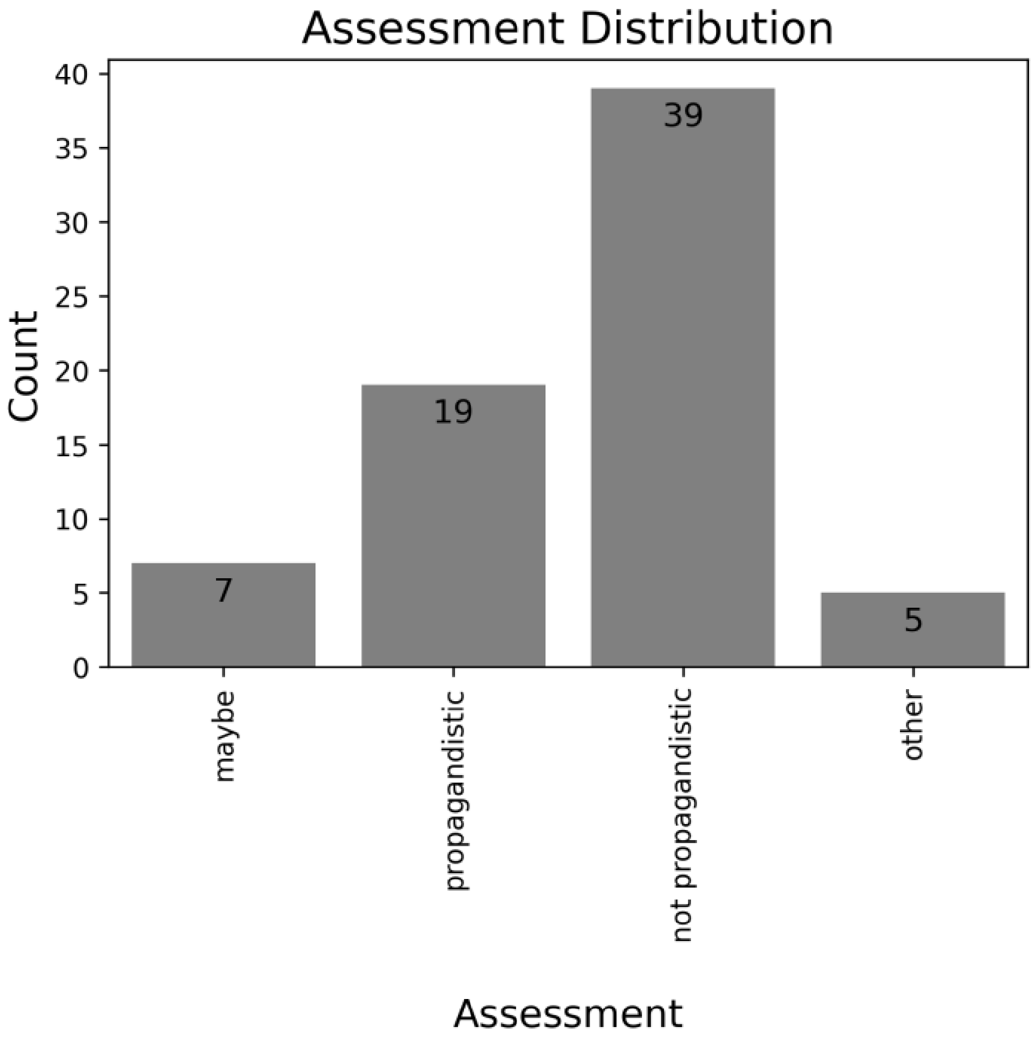


Sejm vs TikTok

sentiment by club

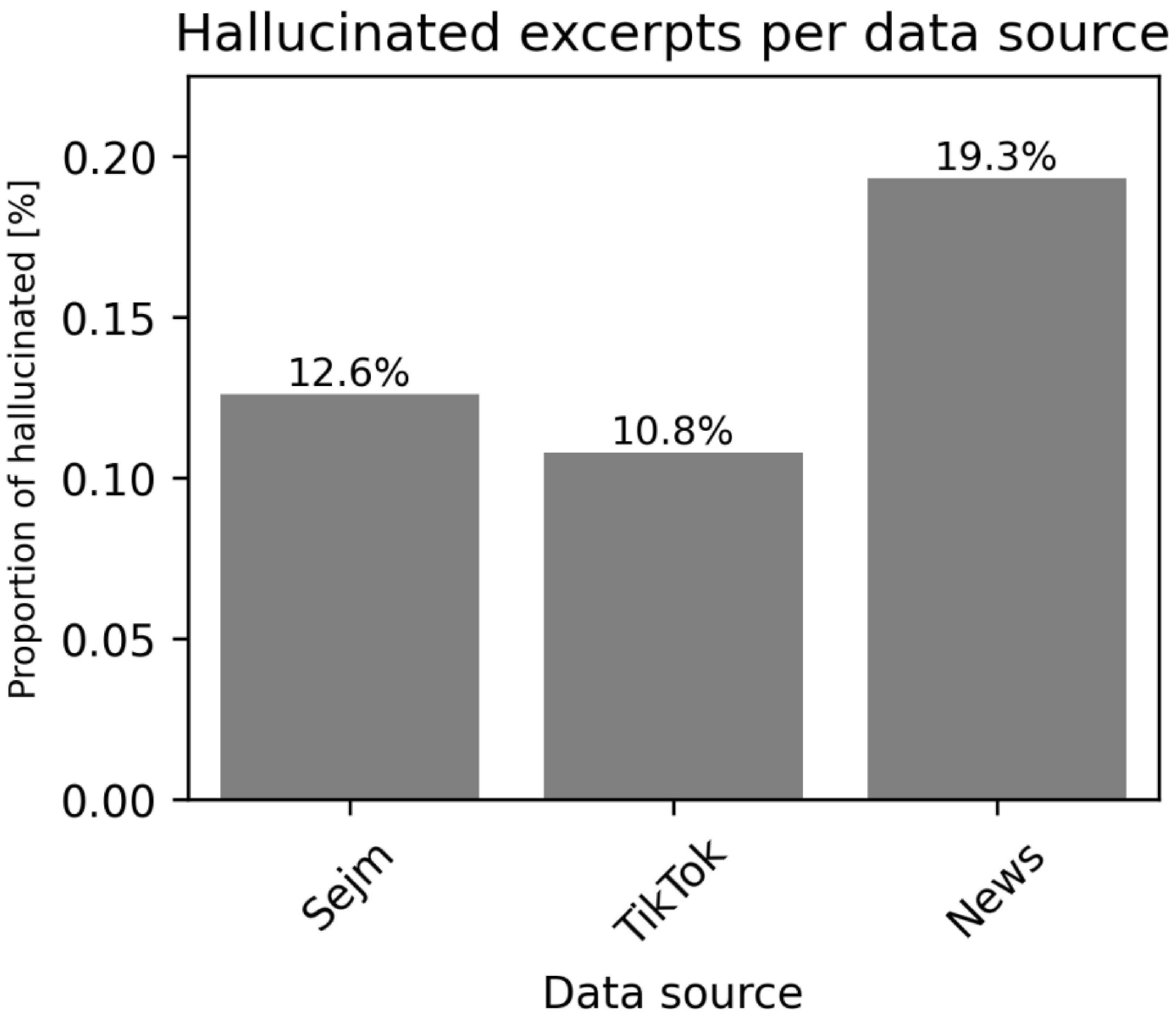


Are the extractions propagandistic?



*The **other** category is for data that was hallucinated (extracted excerpt was not in the article text)*

Hallucination rates



Future improvements

Reduce hallucinations

Improve extractions to be propagandistic

Summary

Developed model: TOP 4 in the competition (our: F1=18.81, SOTA: F1=24.88)

- Larger models are better
- Higher ranks and epochs (to a point) are better

3 datasets analysed

- TikTok, Sejm, News
- Clear trends across techniques (sentiment and frequencies)
  - Flag-Waving – positive, Name-Calling – negative
  - More Flag-Waving in Polish sources than training set

High hallucination rates

Most extractions are not propagandistic

Other sources

- [1] Merriam Webster Online Dictionary. Definition of PROPAGANDA, November 2024. URLhttps://www.merriam-webster.com/dictionary/propaganda.
- [2] CIA and Committee For National Morale. REPORT ON GERMAN MIN-ISTRY OF PROPAGANDA, 1942. URL https://www.cia.gov/readingroom/docs/CIA-RDP13X00001R000100170005-1.pdf.
- [3] Sarah Schneider-Strawczynski and Jérôme Valette. Media Coverage of Immigration and thePolarization of Attitudes. SSRN Electronic Journal, 2023. ISSN 1556-5068. doi: 10.2139/ssrn.4673964. URL https://www.ssrn.com/abstract=4673964.
- [4] United Nations High Commissioner for Refugees. Ukraine Refugee Situation, 2024. URLhttps://data.unhcr.org/en/situations/ukraine.
- [5] Alberto Barrón-Cedeño, Giovanni Da San Martino, Israa Jaradat, and Preslav Nakov.Proppy: A System to Unmask Propaganda in Online News, December 2019. URL http://arxiv.org/abs/1912.06810. arXiv:1912.06810.
- [6] Giovanni Da San Martino, Alberto Barrón-Cedeño, Henning Wachsmuth, Rostislav Petrov,and Preslav Nakov. SemEval-2020 Task 11: Detection of Propaganda Techniques in NewsArticles. In Aurelie Herbelot, Xiaodan Zhu, Alexis Palmer, Nathan Schneider, JonathanMay, and Ekaterina Shutova, editors, Proceedings of the Fourteenth Workshop on Se-mantic Evaluation, pages 1377–1414, Barcelona (online), December 2020. InternationalCommittee for Computational Linguistics. doi: 10.18653/v1/2020.semeval-1.186. URLhttps://aclanthology.org/2020.semeval-1.186.
- [7] Nicolas Michaud. Inappropriate Appeal to Authority. In Bad Arguments, pages 168–171.John Wiley & Sons, Ltd, 2018. ISBN 978-1-119-16581-1. doi: 10.1002/9781119165811.ch32.URL https://onlinelibrary.wiley.com/doi/abs/10.1002/9781119165811.ch32. Sec-tion: 32 _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/9781119165811.ch32.
- [8] Melanie B. Tannenbaum, Justin Hepler, Rick S. Zimmerman, Lindsey Saul, Samantha Ja-cobs, Kristina Wilson, and Dolores Albarracin. Appealing to fear: A Meta-Analysis of FearAppeal Effectiveness and Theories. Psychological bulletin, 141(6):1178–1204, November31BIBLIOGRAPHY2015. ISSN 0033-2909. doi: 10.1037/a0039729. URL https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5789790/.
- [9] Stephen Law. Thinking tools: The bandwagon fallacy. Think, 4(12):111111, 2006. doi:10.1017/S1477175600001792.
- [10] Taeda Tomi. False Dilemma: A Systematic Exposition. Argumentation, 27(4):347–368,November 2013. ISSN 1572-8374. doi: 10.1007/s10503-013-9292-0. URL https://doi.org/10.1007/s10503-013-9292-0.
- [11] Géraud Faye, Benjamin Icard, Morgane Casanova, Julien Chanson, François Maine,François Bancilhon, Guillaume Gadek, Guillaume Gravier, and Paul Égré. Exposing pro-paganda: an analysis of stylistic cues comparing human annotations and machine classifica-tion. In EACL Workshop on Understanding Implicit and Underspecified Language (UnIm-plicit 2024), Malta, Malta, March 2024. URL https://hal.science/hal-04443096.
- [12] Ekaterina Vlasova. Exaggeration in a Political Text (On the Material of Modern Britishand American Newspapers), September 2021. URL https://papers.ssrn.com/abstract=3932128.

Other sources

- [12] Nicole Hein. Spinning Coverage: An Analysis of The New York Times' Reporting on theWar in Iraq in Light of the U.S. Administration's Spin and Propaganda Efforts. GRINVerlag, November 2011. ISBN 978-3-656-04831-2. Google-Books-ID: XuAwGd4PH5oC.
- [13] The Britannica Dictionary. Flagwaving Definition & Meaning | Britannica Dictionary. URLhttps://www.britannica.com/dictionary/flag%E2%80%93waving.
- [14] M. Murray and N. Kujundzic. Critical reflection: A textbook for critical thinking. CriticalReflection: A Textbook for Critical Thinking, pages 1–516, 04 2005.
- [15] Arkadiusz Cezary Sokolnicki. CURRENTS: A Journal of Young English Philology Thoughtand Review. Vol. 5: Periphery: Against the Mainstream:16–40, 2019.
- [16] The Britannica Dictionary. Ad hominem | Definition, Fallacy, Bias, Examples, & Facts |Britannica, November 2024. URL https://www.britannica.com/topic/ad-hominem.
- [17] Merriam-Webster Dictionary. Definition of RED HERRING, December 2024. URL https://www.merriam-webster.com/dictionary/red+herring.
- [18] Thomas Fleming. Reductio ad Hitlerum. JHR Archive, 19(5):24, 2000. URL https://www.historiography-project.com/jhrchives/v19/v19n5p24_reductio.php.32Bibliography
- [19] Gabriel H. Teninbaum. Reductio ad Hitlerum: Trumping the Judicial Nazi Card, 2009.URL https://papers.ssrn.com/abstract=1445423.
- [20] T. C. Winebrenner. Argumentation and debate: Critical thinking for reasoned decision mak-ing. by austin j. freeley. Argumentation and Advocacy, 27(3):137–140, 1991. doi: 10.1080/00028533.1991.11951518. URL https://doi.org/10.1080/00028533.1991.11951518.
- [21] Merriam-Webster Dictionary. Definition of SLOGAN, December 2024. URL https://www.merriam-webster.com/dictionary/slogan.
- [22] Merriam-Webster Dictionary. Definition of STRAW MAN, October 2024. URL https://www.merriam-webster.com/dictionary/straw+man.
- [23] Australian Psychology Society. Explaining thought-terminating clichesand why we should be wary of them | APS, 2024. URL https://psychology.org.au/about-us/news-and-media/aps-in-the-media/2024/explaining-thought-terminating-cliches-and-why-we.
- [24] Britannica Dictionary. Whataboutism | Definition, Examples, Etymology, Logical Fal-lacy, Politics, & Facts | Britannica, December 2024. URL https://www.britannica.com/topic/whataboutism.
- [25] Merriam-Webster Dictionary. Definition of WHATABOUTISM, December 2024. URLhttps://www.merriam-webster.com/dictionary/whataboutism.
- [26] B. Polonijo, S. uman, and I. imac. Propaganda detection using sentiment aware ensemble deep learning. In 2021 44th International Convention on Information, Communication andElectronic Technology (MIPRO), pages 199–204, 2021. doi: 10.23919/MIPRO52101.2021.9596654.