Overview of the CLEF-2023 CheckThat! Lab Task 3 on Political Bias of News Articles and News Media

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Abstract
We provide an overview of task 3 of the CheckThat! lab from the Cross-Language Evaluation Forum (CLEF) 2023, which focuses on predicting the political leaning of English-language news articles and news media outlets. We describe the data collection, the task setup, the evaluation outcomes, and the approaches used by the participating teams. A total of six teams submitted runs for the two subtasks. The top-performing system in Subtask 3A achieved a Mean Absolute Error (MAE) of 0.473, while the best system in Subtask 3B yielded a MAE of 0.549. We make all datasets and evaluation scripts available to the public, aiming to boost further research on this problem.

Keywords
Political bias, news articles, news media.

1. Introduction

In the era of widespread digital information, the impact of political bias in news media and news articles has emerged as a significant concern for democratic societies [1]. Accusations of bias against news organizations, which could influence the public opinion and the policy discourse, have been longstanding [2]. Various research approaches have been used to detect the potential bias of news articles, e.g., by using a headline attention network [3] or by monitoring the frequency of mentions and quotes of politicians from different political parties [4]. At the medium level, a number of recent studies [5, 6, 7, 8, 9, 8, 10, 11, 12] have been conducted, making use of variety of information sources ranging from news articles to tweets, YouTube channels, and user overlap.

To enhance social awareness and to counteract the spread of false information, the CheckThat! lab at CLEF [13, 14, 15, 16, 17, 18, 19] has developed tasks using high-quality data and suitable evaluation measures. As part of this initiative, the CheckThat! lab organizers have offered five distinct tasks [20, 21, 22].

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In this paper, we provide an overview of Task 3, which focuses on detecting the political leaning of *news articles* and *media outlets*. We release high-quality, manually annotated data for these two subtask, based on a 3-point ordinal scale for modeling the bias at the article and at the medium level.

The remainder of this paper is organized as follows: In Section 2, we outline the task at hand and describe the dataset we created and released. Section 3 offers a comprehensive overview of the evaluation settings. We discuss the results and we delve into the details of the submitted systems in Section 4. Section 5 brings to light previous and recent work that aligns with our study. Finally, Section 6 presents our concluding observations and suggests directions for future research.

2. Task and Datasets

Below, we define the tasks, and then we discuss the datasets.

2.1. Task definition

The goal of the task is to detect the political bias of news reporting at the article and at the media level. This is an ordinal classification task and it is offered in English. It includes two subtasks, defined below.

Subtask 3A: Political Bias of News Articles Given an article, classify its political leaning as left, center, or right.

Subtask 3B: Political Bias of News Media Given the news article(s) a news outlet (e.g., www.cnn.com), predict the overall political bias of that news outlet as left, center, or right.

2.2. Datasets

Below, we describe the datasets for the two subtasks.

2.2.1. Subtask 3A

We release a new dataset, which we crawled from AllSides[1], a website that gathers news articles from a variety of reputable national and international news sources to ensure a balanced representation across different political spectrums. The site offers meticulous annotations of the bias of news articles, including expert assessments, third-party analysis, independent evaluations, and community input. In addition, AllSides uses annotated articles to support its Balanced Search tool, which displays the news coverage of a specific issue from numerous media providers, each with a different political bias from all political perspectives, as depicted in Figure 1.

To ensure that the dataset remains relevant and reflects the current political environment, it includes news articles published from late 2022 till early 2023. Each article has several attributes, as shown in Table 1. In total, we have just over 55k articles in the dataset. We provide statistics about the dataset in Table 2.

[1] www.allsides.com

Figure 1: Examples of news articles with bias labels assigned by AllSides (Subtask 3A). Source: www.allsides.com

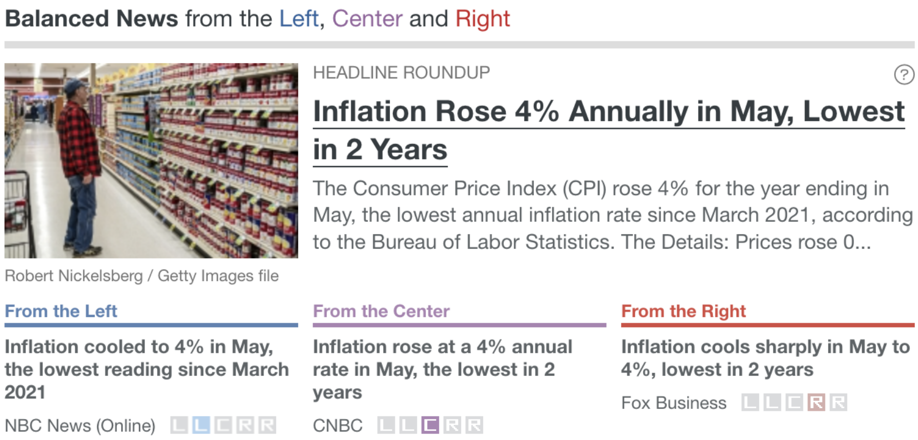

Table 1
Data attributes for the article (Subtask 3A).

ID	Unique identifier
Title	Headline
Content	Full text of the article
Label	Political bias of the article: left, center, or right

Table 2
Statistics about the training, development, and test partitions (Subtask 3A).

	Left	Center	Right	Total
Train	12,073	15,449	17,544	45,066
Dev	1,342	1,717	1,949	5,008
Test	2,589	1,959	650	5,198
Total	**16,004**	**19,125**	**20,143**	**55,272**

2.2.2. Subtask 3B

We assess the political bias of English-language media, sourced from Media Bias/Fact Check website.[2] On that website, experts conduct an in-depth analysis and annotate the political bias of entire news outlets: examples are shown in Table 3. We further include a certain number of articles, which we crawl from each media source: these are to be used by the participants to analyze that source. The dataset has similar attributes to subtask 3A, plus the source (the name of the medium) as an additional attribute. We have over 8,000 articles (approximately 10 per source) and over 1,000 news sources. Tables 4 and 5 show the label distribution and the number of articles and news media.

[2]www.mediabiasfactcheck.com

Table 3
Examples of news outlets and their biases (Subtask 3B).

Left	Center	Right
The Guardian	BBC News	Fox News
The New York Times	Reuters	The Daily Caller
The Washington Post	The Associated Press	The National Review

Table 4
Statistics about the training, the development, and the test partitions for the news outlets (Subtask 3B).

	Left	Center	Right	Total
Train	216	296	305	817
Dev	31	34	39	104
Test	25	29	48	102
Total	**272**	**359**	**392**	**1,023**

Table 5
Statistics about the training, the development, and the test partitions for news articles across all news outlets (Subtask 3B).

	Left	Center	Right	Total
Train	1,350	1,822	2,051	5,223
Dev	378	386	434	1,196
Test	526	536	564	1,626
Total	**2,254**	**2,744**	**3,049**	**8,047**

3. Evaluation Settings

Settings The evaluation comprises development and test phases. During the development phase, we provided the participants with the training and the development sets. This enabled them to internally validate their systems and to adjust the parameter values using the development set. During the test phase, the participants submitted their system's predictions for the provided test set, which did not include reference labels. They were allowed to submit as many runs as they wanted, but only the last submission was considered as the final one.

Evaluation This is an ordinal classification task, and thus we used mean absolute error as the official measure for both subtasks.

Table 6
Results on the leaderboard: political bias of news articles and news media (MAE score).

Subtask 3A			Subtask 3B		
Rank	**Team**	**MAE**	**Rank**	**Team**	**MAE**
1	Accenture [24]	0.473	1	Accenture [24]	0.549
2	TOBB ETU [25]	0.646	2	Awakened	0.765
3	KUCST	0.736	3	Baseline	0.902
4	Awakened	0.752			
5	Baseline	0.877			
	Frank [23]	0.270		Frank [23]	0.320

4. Results and Overview of the Systems

4.1. Results

Table 6, shows the results for Task 3, in which four official teams and one non-official team participated. All teams outperformed the baseline.

Four teams participated in Subtask 3A, with Accenture taking the lead, having the lowest MAE of 0.473. They are followed by *TOBB ETU, KUCST*, and *Awakened* with MAE scores of 0.646, 0.736, and 0.752, respectively.

Two teams took part in Subtask 3B. Once again, Accenture was first, with a MAE of 0.549, followed by Awakened, with a MAE value of 0.765.

Team Frank [23], which did not officially appear on the leaderboard, outperformed all other teams on both subtasks. They achieved a MAE of 0.270 for subtask 3A and 0.320 in subtask 3B. Both scores are much lower than those of the participating teams.

4.2. Overview of the Systems

Accenture [24] used machine back-translation to augment the minority classes examples and thus to address the class imbalance. Then, they fine-tuned RoBERTa on this augmented data.
TOBB ETU [25] used zero-shot and few-shot classification with ChatGPT exclusively for subtask 3A.
Frank [23] used CatBoost, TF.IDF, oversampling, and an ensemble. They had a file formatting issue, and thus they are not officially on the leaderboard.

5. Related Work

The detection of political bias in news articles and media has been the subject of several studies [7, 26, 27, 28, 29] due to its significance in ensuring balanced information dissemination and supporting media literacy [30].

Historically, bias was primarily understood as coverage inequality, as put forth by Stevenson et al. [31]. However, later definitions expanded to include systematic favoring of particular ideologies or candidates, as illustrated by Waldman and Devitt [32].

These broader interpretations of bias consider factors like visual favorability in news images. Based on a review of numerous studies, [33] proposed three types of media bias: gatekeeping bias, coverage bias, and statement bias. Groeling [34] influenced this classification concept of media bias, focusing on selection bias (what to cover) and presentation bias (how to cover it). Selection bias research typically involves collecting news articles or transcripts, analyzing their content, and identifying systematic biases. Meanwhile, presentation bias is often evaluated through framing, visuals, tone, and sources [35]. Multiple methods have been proposed to quantify news slant, including analyzing the language used by different political parties and mapping the distances between media sources based on their mutual followers on social media platforms like Twitter [36, 37, 29].

There have been various approaches for detecting the political bias of news articles. Kulkarni et al. [38] used an attention-based multi-view model. Baly et al. [11] used adversarial training to make sure that the model learns to predict the bias rather than the source of the news article.

Another related task is hyper-partisan news detection, e.g., [39] proposed a meta-learning approach to model the style similarities between text categories [40]. Systems using averaged word embeddings from pre-trained ELMo models succeeded for this task [41].

Efforts to predict the political ideology of news media used multimodal deep-learningDinkov et al. [9]. Fact-checking methods that assess a document's stance towards a claim considering the source's credibility have also been explored [26, 28]. For assessing entire news outlets, researchers modeled tweets and Twitter users [10], information from social media, YouTube, and Wikipedia [8], and inter-media similarity based on audience overlap [12]. There have also been attempts to model bias and factuality jointly in a multitask setup [7].

The `CheckThat!` lab for CLEF has expanded its task offerings compared to the previous iterations, particularly concentrating on check-worthiness [42], subjectivity [43], bias (this paper), factuality [44], and authority [45]. Notably, only in this sixth edition of the `CheckThat!` lab a task has aimed at predicting bias at both the article level and the medium level.

Overall, various computational models and datasets have advanced the detection of political bias and factuality and contributed to media literacy efforts [46, 47, 48].

6. Conclusion and Future Work

We presented a comprehensive analysis of Task 3 from the `CheckThat!` lab at CLEF 2023. This lab focused on detecting the political bias in news articles and media outlets. The submissions used transformer-based models (such as RoBERTa and ChatGPT) and gradient boosting on decision trees (like CatBoost), achieving sizable improvements over the baselines.

In future work, we plan to explore more information sources, to add more languages, and to adopt a finer-grained scale.

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