DATA-DRIVEN NEWS OUTLET BIAS DETECTION WITH GDELT

PATTERNS AND EXPLANATIONS OF NEWS OUTLET POLITICAL BIAS

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Abstract

News and media play a crucial role in informing public opinion, influencing politics, governance, and civic life alike. Although journalism strives for unbiased reporting, various forms of bias may appear throughout the writing and publication process. Previous studies in social and computational sciences have thus attempted to identify news bias. Yet, these methods are often either laborious, require expert knowledge and produce irregular results, or, while being more efficient, focus primarily on detection rather than deeper understanding. Furthermore, previous research has also focused on sentence- or article-level bias, excluding important patterns that emerge from an outlet's behaviour as a whole. Thus, this thesis aimed to classify outlet bias on global data using machine learning, while accounting for multiple forms of bias. The results demonstrated a somewhat successful classification of political bias among news outlets, and incorporating features related to less-studied forms of bias improved model performance, yielding the best performing model with a 75% accuracy and AUC of 81 (compared to a baseline of 45% and 50 AUC). Furthermore, this approach includes Shapeley Additive Explanations (SHAP), which provides explanations and transparency into the model's reasoning and indicates underlying processes of biased news outlet behaviour. This presents a scalable and comprehensive approach to studying news political bias.

1 INTRODUCTION

The Joint Research Centre of the European Commission notes that "[a] functioning democracy depends on the ability of its citizens to make informed decisions" (Lewandowsky et al., 2020). News and media play a crucial role in informing public opinion, influencing politics, governance and civic life (Hamborg, Donnay, & Gipp, 2019; Kelsey, 2019). While journalism generally strives towards impartial reporting of events, this

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APPENDIX A: MBFC FEATURES

This appendix describes in more detail the features provided by MBFC. For each news outlet, they provide a set of data points of interest:

- Political lean, which denotes whether a news outlet will tend to favor either the left or right political spectrum. This feature contains five classes in total: "left", "left center", "least biased", "right center" and "right" leaning. They compile a set of principles for determining whether a source is left or right leaning, which can be found on their website for further information (Media Bias Fact Check, 2021b).

- Factuality refers to how factual a source tends to be, whether they use credible sources, immediately correct incorrect information and have failed credible reporting fact-checks in the past. The categories span from "very low", "low", "mixed", "mostly factual", and"high" to "very high". Details of how these are evaluated are explained in their methodology.

- Traffic estimates are drawn from Similar Web to determine the amount of visitors each news outlet site receives, accounting for page views, print and media market viewers per month. An outlet with under 150 thousand views per month is classed as having minimal traffic, 150 thousand to 2.5 million as medium traffic and anything above is denoted as high traffic.

- Country press freedom is also noted on the site, as measured by the World Press Freedom Index by Reporters without Borders (Borders & French, 2022). They use each country's rank to determine their score: top ten countries receive an "excellent" score, those until top 50 a "mostly free" score, top 100 are considered to have "moderate freedom", top 160 "limited freedom" and the remainder are classed as "oppressed". There are a total of 180 countries ranked.

- Media type records which types of media the news outlet in question uses. This includes many often overlapping categories that were simplified into the following classes: website, TV station, radio station, journal, magazine, news agency, news paper and organisations/foundations.

- The credibility rating is a combination of some of the above mentioned features. It combines the factuality score with the traffic, political lean magnitude and press freedom scores to determine a final rating, ranging from "high credibility","medium credibility" to "low credibility".