Media Slant as Political Refraction

Measuring the Ideological Diversity of the French Media Landscape

Keywords : Media Slant; Natural Language Processing; Politics; Deep Learning; Media Studies

The last twenty years saw the return of an old question in the human and social sciences: that of the media bias. This perpetual accusation regained steam for a set of variegated reasons. Some have to do with the increased data availability, which makes it easier to collect and analyse textual traces (Grimmer, Roberts, Stewart, 2022, pp. 3-4). Another one has to do with some rapid transformations the media sector underwent, as it was impacted by the development of the internet, dwindling revenues, and by a series of buyouts by magnates -- some of them with an explicit political agenda.

This question of public interest was largely invested by scholars, qualitative and quantitative alike. Among the latter, some proposed measures of this "media slant". To wit, three types of approaches were used. One line of research is premised on external information, such as the endorsements made by the newspaper (Chiang and Knight, 2011), or the declared political leaning of their audience (Fletcher, Robertson and Nielsen, 2021). Other approaches pay more attention to the content. One is based on the identity of the persons invited by the outlet to express their opinion (Durante and Knight, 2012; Groseclose and Milyo, 2005; and recently Cagé, Hengel, Hervé, and Urvoy, 2022). After being detected, individuals are subsequently scored according to their political affiliation, and a general value bias is provided – by outlet, by show, etc. Yet another very popular approach relies on the text produced by media outlets. In this case, the focus is placed on the text (or snippets of it), whose political leaning is then evaluated. The method can be mostly automated (see Gentzkow and Shapiro, 2010 for a seminal text using this method), or it can be outsourced to research assistants (Baum and Groeling, 2008).

All of these approaches have undeniably contributed to our understanding of media slant, as they helped to document the evolution, to track the actors and to expound the causes of this phenomenon. Yet the analyses often rely either on very limited data, or on strong assumptions, and sometimes on both.

By contrast, this paper offers an easy to implement, inductive method to document this classic question of the media slant. We take advantage recent advances in natural language processing to propose a method that is based on the analysis of the complete archive of the newspapers. Taking cues from social scientific studies of news media production, we also introduce a strategy to efficiently classify content from various media reports. Our approach relies on Transformers models. A set of deep learning techniques using a self-attention mechanism, Transformers have gained massive attention since their introduction at the end of the last decade (Vaswani *et al.*, 2017), since they demonstrated their ability to accurately annotate millions of texts in a short period of time (Do, Shen and Ollion, 2022).

Equipped with these models, we train classifiers to detect media bias. To do so, we leverage a classic insight from journalism studies, according to which journalists do not differ so much by what they say, but rather by how they say it. Due to a set of journalistic norms, political opinions are less stated explicitly than they are refracted in the choice of angles. We operationalize this remark by training BERT models that detect a more 'liberal" and more "conservative" approach on a set of topics, in the main daily French newspapers.

We demonstrate the reliability of our approach using purely quantitative indicators in the form of F1-scores (*table 1*), along with qualitative approaches. We show that the models captures well known ideological variations (*Figure 1*), which we further interpret. For instance, the right-wing turn evoked by many and feared by some is not obvious. On certain topics, such as LGBT rights, the trend is even the opposite – a sign that the explicit pathologization of LGBT persons, still a possibility in some mainstream newspapers in the late 1990s, is not seen as a legitimate argumentation anymore. On other topics, the gap widens between newspapers, pointing to a rising polarization between outlets.

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Figures and Tables

Table 1: Quality Measures for Each classifier

Expressed as F1-Scores (confidence intervals between brackets)

	F1-Angle 1 (~ Liberal)	F1-Angle 2 (~Conservative)	F1-Other
Immigration	0.73 (0.72, 0.75)	0.66 (0.65, 0.67)	0.85 (0.84, 0.86)
Taxes	0.81 (0.72, 0.90)	0.72 (0.64, 0.80)	0.92 (0.91, 0.93)
LGBT	0.73 (0.72, 0.74)	0.74 (0.73, 0.75)	0.94 (0.93, 0.94)

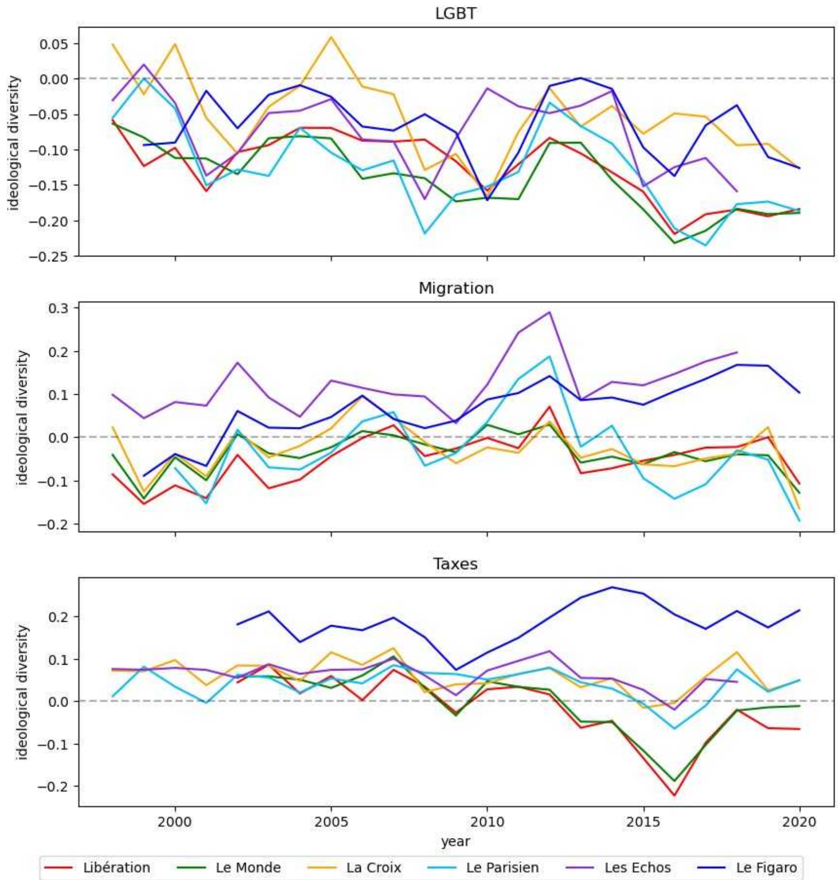

Figure 1. Ideological Divergence on three selected topics for the main daily newspapers in France (2000-2022)