# Connecting the Dots in News Analysis: A Cross-Disciplinary Survey of Media Bias and Framing

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## Abstract

The manifestation and effect of bias in news reporting have been central topics in the social sciences for decades, and have received increasing attention in the NLP community recently. While NLP can help to scale up analyses or contribute automatic procedures to investigate the impact of biased news in society, we argue that methodologies that are currently dominant fall short of addressing the complex questions and effects addressed in theoretical media studies. In this survey paper, we review social science approaches and draw a comparison with typical task formulations, methods, and evaluation metrics used in the analysis of media bias in NLP. We discuss open questions and suggest possible directions to close identified gaps between theory and predictive models, and their evaluation. These include model transparency, considering document-external information, and cross-document reasoning rather than single-label assignment.

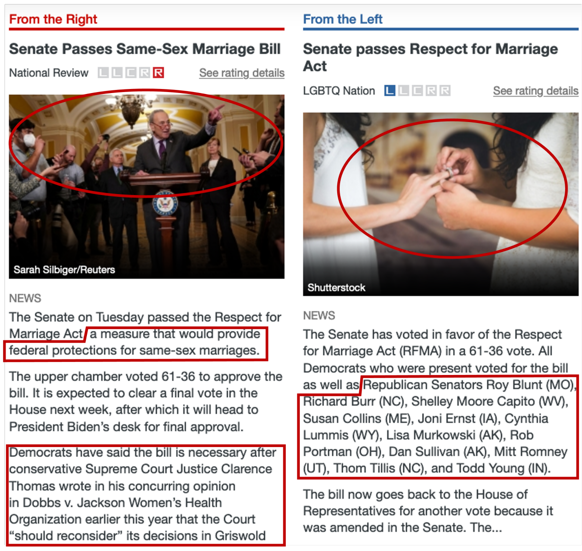


Figure 1: Two articles about the same event written from different political ideologies. Example taken from AllSides.com.

## 1 Introduction

The depiction of complex issues in the media strongly impacts public opinion, politics, and policies (Ghanem, 1997; Giles and Shaw, 2009). Because a handful of global corporations own an increasing proportion of news outlets, the reach and impact of biased reporting are amplified (Hamborg, 2020). Although perfect neutrality is neither realistic nor desirable, media bias turns into an issue when it becomes systematic. If the public is unaware of the presence of bias, this can lead to dangerous consequences, including intolerance and ideological segregation (Baly et al., 2020).

For decades, news analysis has been an active field of research in the social sciences, and more recently, computational methods for framing and political bias classification have gained considerable momentum. The increasing pace of news reporting suggests a need to scale the process of media bias detection, and there is evidence that exposing media bias promotes healthy public debate, helps journalists to increase thoroughness and objectivity, and promotes critical and conscious news consumption (Dallmann et al., 2015). In the context of this paper, we see the role of NLP as helping to understand, characterise and expose bias at scale.

Figure 1 illustrates the concepts of 'framing' and 'media bias' adopted in this paper, using the passing of the Respect for Marriage Act as an example. *Framing* refers to the deliberate presentation or emphasis of selected facts with the goal of eliciting a desired interpretation or reaction in the reader (Entman, 2007). The left-leaning article in Figure 1 leads with an uplifting picture of a wedding and emphasizes bill support, evoking a positive framing by emphasizing new opportunities for same-sex couples; while the right-leaning article focuses on concerns and debates in both image and text, framing the issue in the a more negative light. *Political bias* refers to partisan slanted news stories, or the "tendency to deviate from an accurate, neutral, balanced, and impartial representation of 'reality' of events and social world" (McQuail and Deuze, 2020), which can be a result of a selected framing. In Figure 1, each document was flagged as far-left and far-right ideological leaning, respectively, as a result of the different attitudes and selected points of emphasis chosen in the reporting. Political bias is typically deliberate (Williams, 1975) while framing may be inadvertent as a result of focusing on selective information due to external pressures such as space limitations.

In this paper, we survey work on framing and media bias prediction in NLP and relate it to typical research questions and hypotheses in the social sciences. We tease out disconnects across disciplines, and make concrete suggestions on how social science approaches can improve NLP methodology, and how NLP methods can more effectively aid both social science scholars in their analyses as well as underpin tools and applications to raise awareness of media bias among the general public.

## 2 Background

### 2.1 Framing and Media Bias

We focus on the widely-studied phenomena of *framing* and *political bias*, as they support the detection of partisan-biased documents, and both framing and media bias are strategies to promote a particular view about a specific topic.

A variety of definitions of *framing* exists in social science and communication studies. Prevalent definitions include *equivalence framing:* presenting the same logical information in different forms (Cacciatore et al., 2016) and *emphasis framing:* highlighting particular aspects of an issue to promote a particular interpretation (Entman, 2007). Additionally, framing has been conceptualised as a process (de Vreese, 2005; Entman, 2007; Chong and Druckman, 2007), a communication tool (Scheufele, 1999), and/or a political strategy (Roy and Goldwasser, 2020). In order to identify and classify frames automatically, it can be helpful to understand the 'generative process' of frames. Frames can be conceptualised into different typologies, e.g. de Vreese (2005) proposes *issue-specific:* only pertinent to a single matter, and *issue-generic:* identifiable across several issues. While Scheufele (1999) differentiates between *media frames:* embedded in the political discourse, and *audience frames:* the reader's interpretation of an issue. And Gross (2008) defines *episodic framing* as portraying an issue with an individual example compared to *thematic framing*, which takes a more broader context to describe the same issue. In this manuscript we cover both issue-specific and issue-generic frames and attach to de Vreese (2005)'s definition of a frame as "an emphasis in salience of different aspects of a topic".

Political bias refers to an explicit association of a news article or media outlet with a specific political leaning. Although framing and political bias are different phenomena, NLP researchers have attempted to address them jointly, either by investigating political framing (Roy and Goldwasser, 2020) or by identifying correlations between framing and partisan slanted articles (Ziems and Yang, 2021). NLP studies have attempted automatic media bias identification under several names, including: hyper-partisan news detection (Kiesel et al., 2019), media bias detection (Spinde et al., 2021b; Lei et al., 2022), identification of biased terms (Spinde et al., 2021a), and political ideology detection (Iyyer et al., 2014; Kulkarni et al., 2018). Their common goal is to detect and classify the bias of a data sample towards a particular political ideology. Many of these approaches naturally relate to investigate *how the story is told* (framing).

### 2.2 Why is this Survey Relevant?

Hamborg et al. (2019) present a thorough overview of traditional and computational approaches to media bias, including detailed definitions of bias types and their emergence in the context of news production. We complement the survey by providing a more in-depth review of research methodologies in NLP, more recent computational approaches, and a unified focus on the phenomenon of framing and its manifestation as media bias. A very recent survey by Ali and Hassan (2022) reviews computational approaches to modelling framing providing a detailed systematic analysis of NLP methods.

For an exhaustive list of NLP previous work we refer the reader to Ali and Hassan (2022). In contrast, our survey takes a closer look at the overall NLP pipeline: data, methodology, and evaluation; draw connections to social science methodology; and pinpoint the gaps between the two disciplines. In order to obtain a comprehensive body of literature which bridge the domains,[1] we departed

[1] Here, we do not follow the standard approach of selecting the top $N$ results from Google Scholar or the ACL Anthology for a simple query, as work in this space is published under many different names in a myriad of venues.

from influential cross-disciplinary papers: (1) a review of media bias and framing across disciplines, but with no focus on state-of-the-art NLP (Hamborg et al., 2019); and (2) one of the first and most influential NLP framing data sets, with a strong theoretical grounding (Card et al., 2015). We identified other relevant work by following both papers' citation graphs (both backwards and forwards).

## 3 Three Disconnects

To illustrate the disconnects between the social sciences and NLP, we use the case study of Hernández (2018)'s study of the framing of domestic violence, in which the author formulates two research questions:

1. Framing functions: Are femicides recognized as a problem of domestic violence? What are the causes of femicides? And what are the solutions proposed?
2. Frame narratives: What are the main narratives of the SCMP[2]? And what are the sources used to report them?

The first research question considers the *local* aspects within each news article. Specifically, it looks at the causes and solutions presented, grounded in Entman (1993)'s conceptualisation of framing in terms of a problem, its cause, and its solution. The second research question relates these local aspects to a *global* view by contrasting narratives that present domestic violence as isolated incidents with those that treat it as a societal problem. They connect the news reports to *extrinsic* variables like the sources used or the cultural context of the story e.g. whether the article refers the role of women in the Chinese family or understands domestic violence through the lens of the Confucian philosophy. Their study considers full articles over an extended period, capturing the *temporal development* of framing of the issue. In contrast, current NLP approaches to frame prediction: (a) typically take a single-class prediction approach —with a few exceptions (Akyürek et al., 2020; Mendelsohn et al., 2021) — per unit of analysis (sentence or article), rather than treating frames as more complex structures which could for instance distinguish aspects such as cause vs. solution; and (b) treat units of analysis as independent without explicitly drawing connections across articles, or across time, or to document-external context.

We thus highlight three important aspects of framing that we could identify while reviewing social science literature. These aspects emerge in theoretical media studies, but cannot be modeled through (single-label) classification, and consequently not attainable by most current NLP approaches:

**Framing is local and global** It is local, because because a single document can contain several frames, and it is global because to understand the general framing of an article it is often necessary to (a) aggregate local frames and (b) link them to document-external information such as cited (or omitted) sources, or the outlets' political leaning.

**Framing is dynamic** Frames change over time, across outlets, or across countries or communities. Understanding the *development* of framing can shed light on the impacts of a sustained exposure to biased reporting on readers' opinions, and enables the study of trends.

**Framing as a comparative task** Media bias and framing often become most apparent when directly contrasting articles from different perspectives, places or times (cf., Figure 1). We propose to address bias and frame classification as a comparative task rather than labeling documents in isolation. This can help *inducing* frames from data by analyzing axes of largest variation; and can naturally support tools and applications to raise readers' bias awareness by exposing them to contrasting perspectives on the same issue.

The remainder of this article reviews current practice in NLP, points out disconnects to the social science principles introduced above, and suggests steps towards bridging the gap between the disciplines.

## 4 A Critical Review of Current Practices in NLP and Social Science

In this section we review both sides of the field, NLP and social sciences, especially communication studies. We look at three main aspects, which we consider to be the most relevant criteria when conducting research: datasets, methods, and evaluation and metrics. Here, the reader can find the similarities and differences across both disciplines.

### 4.1 Datasets

Benchmark datasets dominate modern-day NLP research, and news analysis is no exception. In this

[2] South China Morning Post

| Dataset | Categories | Size | Granularity | Task |
|---|---|---|---|---|
| Bitterlemons (Lin et al., 2006) | Israel vs. Palestine | 594 | Documents | Classification |
| Flipper (Chen et al., 2018) | Left, Centre, Right | 6,447 | Documents | Classification |
| BASIL (Fan et al., 2019) | Libe., Cons., Centre; Pos, Neu, Neg | 1.2k / 448 300 | Spans/Words Documents | Classification |
| AllSides (Baly et al., 2020) | Left, Centre, Right | 34k | Documents | Classification |
| BiasedSents (Lim et al., 2020) | not-, slightly-, very-, biased | 966 | Sentences | Classification |
| BABE (Spinde et al., 2021b) | Biased, Non-biased | 3.7k | Sentences | Classification |
| BIGNEWSALIGN (Liu et al., 2022) | Left, Centre, Right | 1M | Documents | Classification |
| NeuS (Lee et al., 2022) | Left, Centre, Right | 10.6k | Documents | Cross-Doc Summarisation |
| MFC (Card et al., 2015) | 15 Frames | 61.5k/ 11.9k | Sentences/ Documents | Classification |
| GVFC (Liu et al., 2019) | 9 Frames | 2.99k | Headlines | Classification |
| Multimodal GVFC (Tourni et al., 2021) | 9 Frames | 1.3k | Headlines + Images | Classification |
| PVFC (Ziems and Yang, 2021) | Entity frames & Cons., Libe., none | 82k | Documents | Entity frame prediction |

Table 1: Benchmark contributions in political bias (top) and framing (bottom) mostly in American English. Categories for BASIL denote liberal, conservative, and centre for partisan labels, and polarity classes represent positive, neutral and negative.

section, we review NLP datasets relating to framing and political bias analysis in the news domain. In Table 1, we list relevant datasets, along with the type of labels they provide, the size of the collection, the associated tasks, and sample granularity, whether words, sentences or documents.

For the media bias detection task at the *sentence level*, Lim et al. (2020) used crowdsourcing to annotate sentences on 46 English-language news articles about 4 different events with four levels of bias (not-biased, slightly biased, biased, or very biased). Spinde et al. (2021b) released BABE ("Bias Annotations By Experts"), a collection of sentences labelled by experts according to binary categories: biased and non-biased, at the sentence and word levels. Fan et al. (2019) contributed the BASIL ("Bias Annotation Spans on the Informational Level") data set which includes word and sentence (span) level annotations of political leaning, as well as sentiment (stance) towards the entities in the article.

At the *document level*, the Bitterlemons corpus (Lin et al., 2006), comprises weekly issues about the Palestine–Israel conflict. Each issue contains articles from Palestinian and Israeli perspectives written by the portal's editors and guest authors. Despite being intended for document classification, this dataset can be employed to explore framing and political bias, given the documents' nature of strong bias towards one side of the conflict.

Additionally, the web portal AllSides[3] categorises articles into three political ideologies: right, centre, and left (they also offer a finer-grained five-point scale annotation: left, lean left, centre, lean right, right) with the aim to provide all political perspectives on a given story (cf., Figure 1). Experts manually assigned categories at the article level. Several research groups have contributed datasets scraped from AllSides (Chen et al., 2018; Baly et al., 2020; Liu et al., 2022; Lee et al., 2022).

In the field of framing at the *sentence (headline) level*, Liu et al. (2019) released the Gun Violence Frame Corpus (GVFC). It includes headlines about gun violence in news articles from 2016 and 2018 in the U.S., labelled with frames like politics, economics, and mental health. Tourni et al. (2021) released a multi-modal version of the GVFC collection, including the main image associated with each article, and annotations about relevance and framing at the image level.

At the *document level*, there is what is probably the most extensive data collection for investigating framing: the Media Frames Corpus (MFC, Card et al., 2015). It includes articles from 13 U.S. newspapers on three policy issues: immigration, same-sex marriage, and smoking. This dataset is intended to enable the analysis of policy issue framing, providing annotations at document and span levels with frames like morality, economic, and cultural. Ziems and Yang (2021) contribute a police violence news articles collection (PVFC) that can be categorised in both domains, media bias and framing. They provide annotations for politi-

[3] https://www.allsides.com/about

cal leaning: conservative, liberal or none and also entity-centric frames, including the victim's age, race, and gender. They also include the code to extract those entity frames automatically using regular expressions. It is pertinent to note that this survey is primarily U.S.- and English-centred, in large part because currently-available datasets and work predominantly focus on U.S. news sources. Diversifying research to other countries, cultures, and languages is an important step for future work.

In Section 3, we propose three main aspects to investigate framing and media bias: (1) conducting studies at a local and global level; (2) considering the dynamics of framing; and (3) addressing the problem as a comparative task. We suggest that despite being intended for document classification, benchmarks like AllSides, MFC, and Bitterlemons can be redeployed to explore framing and political bias in a different fashion. Instead of assigning frames or political ideologies to documents, they could be used to examine framing and political bias by extracting the most common expressions for each frame or ideology, and investigating commonalities, which can be helpful to social scientists for local and global analyses. Indicators that have been explored by Roy and Goldwasser (2020) are point-wise mutual information (Church and Hanks, 1990) over bigrams and trigrams, but this approach does not generalise well. The MFC contains sentence-level annotations for exploring local framing, however to the best of our knowledge no study has attempted to aggregate those labels to a global level. Regarding datasets providing sentence-level (BABE) and headline (GVFC) annotation, this can be considered as a local dimension. However, this generalises from the headline to the entire document, which ignores the subtle signals in the local dimension.

With respect to aspect (2), dynamics occur on many levels, some of which are captured by current data sets: the MFC, BASIL, GVFC and BABE provide article timestamps, supporting diachronic modeling of bias and framing. While some studies exist in this domain (Kwak et al., 2020; Card et al., 2022), the majority of NLP framing considers articles in isolation. Other dynamics, e.g., across countries, communities or media types (e.g., news vs. blogs) are of central interest in communication studies but less achievable with existing data sets. Modelling those dynamics is under-explored.

For addressing aspect (3), we propose that researchers explore cross-document differences from various outlets, and their particular angle on a specific issue. Several of the datasets obtained from AllSides include alignment at the event level and hence enable comparison across documents on the left–centre–right spectrum at a finer granularity. A cross-ideology analysis at the event level facilitates the detection of local differences among the three ideologies and allows global aggregation at the document level.

### 4.2 Methods

Researchers in NLP have attempted to tackle media bias as political ideology detection or framing categorisation using different task formulations. The first and most common strategy is *single-label classification*, i.e. assigning a single label to each data point. At the *word level*, Recasens et al. (2013) learn linguistic features from word removal editlogs in Wikipedia. Spinde et al. (2021a) compared the Euclidean distance of word embeddings to identify biased words in articles from Huffington Post (left wing) and Breitbart News (right wing). And Liu et al. (2021) experimented with identifying and replacing bias-inducing words with neutral ones using salience scores over word embeddings.

At the *sentence level*, Iyyer et al. (2014) used RNNs to identify political ideology in sentences in congressional debate transcripts and articles from the Ideological Book corpus. Using the BASIL corpus, Hartmann et al. (2019) correlated sentence and document distributions using a Gaussian mixture model (Reynolds, 2009) to identify biased sentences; Chen et al. (2020) classified biased spans by calculating their probability distributions on news articles; and Guo and Zhu (2022) applied contrastive learning and created sentence graphs to categorise biased sentences. Other researchers translated keywords from GVFC into several languages, and fine-tuned mBERT to classify frames in news headlines in languages other than English (Akyürek et al., 2020; Aksenov et al., 2021).

At the *document level*, there has been substantial work on assigned frames to documents in the MFC corpus. The task has been approached with RNNs (Naderi and Hirst, 2017), attention and discourse information (Ji and Smith, 2017), and pretrained models (Khanehzar et al., 2019). Baly et al. (2020) combined adversarial adaptation and adapted triple loss with features like Twitter and Wikipedia information about the readers and the outlet to classify the political ideology of news articles. Scholars have performed similar tasks on languages other than English, e.g. by translating English keywords in MFC to Russian to investigate the U.S. framing in Russian media over 13 years (Field et al., 2018).

The second formulation is *multi-label classification*. Researchers have primarily used topic modelling (Tsur et al., 2015; Menini et al., 2017) or clustering (Ajjour et al., 2019) to determine the frames present in a document, in an unsupervised setting. Soft membership for topics or clusters allows documents to be assigned to various clusters or topics. Most of this work has been done over political speeches rather than news articles. In a supervised manner, Mendelsohn et al. (2021) employ RoBERTa to classify multiple framing typologies on immigration-related tweets. Similarly, Akyürek et al. (2020) address multi-label framing over headlines using different configurations of BERT. However, all of this work has been done over headlines or documents with a maximum length of 280 characters, and no work has been done at the level of full news articles.

Other related task formulations include *entity framing*. At the document level, Ziems and Yang (2021) use regular expressions to identify entity characteristics (gender, race, age, etc.); and Frermann et al. (2023) explore the co-occurrence of narrative roles (entity pictured as villain, hero, or victim) with frames on manually-annotated climate change data. Finally, NLP researchers have also investigated *bias mitigation*. At the headline level, Chen et al. (2018) used LSTMs to flip the leaning of a headline, for example, from a right-leaning title to a left-leaning one, in an attempt to alleviate bias. However, flipping the ideology does not entail the reduction of bias. At the document level, Lee et al. (2022) aggregate all perspectives in one document using multi-document summarisation. We argue that including all biases does not necessarily reduce the impact of ideology bias. Aggregating the most relevant aspects and presenting them comparatively, as depicted in Figure 1, is more effective and has greater utility for social scientists.

In the social sciences, approaches tend to be manual, with fewer data samples. One common approach is to *reason across many documents from a high-level perspective*. For example, Chyi and McCombs (2004) design and evaluate a two-dimensional framework (spatial and temporal) to investigate framing changes over time in 170 news articles in American English about a U.S. school shooting event. They manually annotated articles with the signals indicating both of the frame typologies, quantified those annotations and draw conclusions about the temporal and spatial framing behaviour in the inspected articles. Muschert and Carr (2006) assessed the previously-proposed framework based on 290 news documents, and confirmed that the present temporal dimension frame still holds when using data from more than one school shooting. Hernández (2018) analysed the framing of 124 news stories from the South China Morning Post (SCMP) about femicides by manually coding the articles and quantifying those observations. The author explored whether those cases were portrayed as isolated cases or part of a systematic social problem, by manually analysing signals like narratives, sources, and the role of the entities.

In addition, communication science studies often *correlate features of news reports with extra-textual information to formulate or validate their hypotheses* (see also Hamborg et al., 2019). For example, McCarthy et al. (2008) investigate whether the media is ideologically biased in reporting about demonstration events. They track media coverage of protests during the transition period from communism in Belarus by considering features like the size of the protest, sponsors' status, and number of arrests, and examine their correlation with the event's media coverage. Similarly, Gentzkow and Shapiro (2010) investigate media bias by calculating citations of different media outlets by think tanks, and correlating those statistics with the number of times that members of the U.S. Congress mentioned the same groups. Here, we see a stark disconnect between largely *local* frame modelling in NLP but a strong dominance on *dynamic* and *global* questions raised in communication studies. Social science research provides a lens through which to consider NLP methodology, and its insistence on considering each sample in isolation. We argue that learning from signals like the use of metaphoric or technical (legal) language, the correlation with informative features like sources integrated in the report, and the role of the audience and journalist's cultural background in the story all contribute to news framing and bias analysis.

### 4.3 Metrics and Evaluation

We consider two levels of validation: validating data annotations, and validating model predictions.

The former — validating the quality of labelled data — applies to both the social sciences and NLP. In a typical social science study, the distribution of manual labels is the main factor for accepting or rejecting hypotheses or drawing larger conclusions. As such, measures for data quality such as intercoder reliability (ICR) are routinely reported and a core requisite of the study. This validation ensures that the codebook was correctly conceptualised, and coding often includes discussions and several iterations on trial data or pilot studies (Hernández, 2018), leading to relatively high ICR scores from carefully trained annotators, often with domain knowledge.

Social science studies are largely analytical (examining labelled data, qualitatively based on manual analysis, and quantitatively based on statistical tests).

NLP studies on framing are empirical, and evaluation (regrettably) often comes down to numeric comparison of a newly proposed method against previous work, by comparing the predictions of systems against the ground truth frame labels. This does not provide fundamental insights into how well a model can capture framing or political bias at a higher and more abstract level, or whether it is better able to lead to fresh insights into the data. In other words, current approaches fall short of providing inferences from explicit information, i.e. assessing the objectivity of a story as well as measuring the level of factuality by identifying whether a story adopts a recounting or metaphoric style. These strategies are graded in nature (rather than binary) and metrics like accuracy are deficient.

In order to address the above-mentioned issues, we propose that automatic framing and bias analysis evaluation tackle three main points: (1) *model performance*, (2) *error analysis*, and (3) *measuring model certainty*. Even though overall model performance in terms of accuracy or F1 does not provide a complete picture of its utility (Spinde et al., 2021b), we still need to consider point (1) to gauge the overall capabilities of a model. However, we can go deeper and also investigate the performance at the outlet level or look into the most challenging frames for the model to predict. This leads to point (2), error analysis, following previous work (Vilar et al., 2006; Kummerfeld and Klein, 2013), we propose three key components: (a) error categorisation. (b) Scrutinising the potential causes of these errors. (c) Going beyond identification, extending to suggesting feasible strategies for improvement based on the nature and origins of the errors. Finally, we see the role of NLP as developing meaningful tools and methods that can support social science scholars to enhance and scale the investigation of framing and political bias. Therefore, a user should be able to access model confidence scores to assess the reliability of model predictions, as per point (3).

## 5 Discussion

Having reviewed approaches in the social sciences and NLP, and enumerated disconnects, we ask: *What are practices in the social sciences that NLP can adopt?* NLP task formulations tend to focus on assigning a single label (e.g., a frame) to a unit of analysis, typically a document or sentence. Social science studies annotate news excerpts at the local dimension and combine that information with external signals to arrive at higher-level conclusions. Recalling our introductory example on the framing of domestic violence in the SCMP, Hernández (2018) considers the broader impact, incorporating other victims included in the news story (local signals); the role of culture in the article: whether women are portrayed from their role in the Chinese family or the story mentions Confucianism concepts; the type of report: brief or news story; the sources, whether the article is based on a police report (external factors). She combines these signals and aggregates them to the document-level (global perspective) to draw higher-level conclusions on the dominant narrative framing of domestic violence as isolated instances or a societal phenomenon across the entire collection of articles.

With regard to NLP, we argue that the standard practice of assigning a single frame label to news documents is overly simplistic, given that a typical news story comprises viewpoints, arguments, or aspects, which may individually have different connotations or framing. We acknowledge that causes of simplifying annotation relate to factors that affect scalability and automation like the costs and the difficulty of achieving inter-annotator agreement. In these cases researchers are overcoming these challenges by means of few-shot pre-training models (He et al., 2023; Bansal and Sharma, 2023). In the context of political debates, Ajjour et al.

(2019) suggest breaking down debates into arguments and identifying a frame for each idea. Similar strategies in a media framing context could mitigate the simplifying assumption of one frame per article. Khanehzar et al. (2021) also argue that the single, primary frame annotation in the MFC is oversimplified and propose a model for multi-view representations of news stories. To address this gap, we suggest a two-step process: (1) split a news document into self-contained discourse units (such as arguments or events); and (2) assign a frame label to each unit, and/or one or more global frame-label(s) by aggregating across units. As reviewed in Sections 4.1 and 4.2, NLP methods operate mostly on the sentence level (which cannot capture longer arguments) or the document level. Analyzing frames on an argument- or event level reflects the typical level of analysis in the media studies. Rather than assigning the single most likely frame, researchers might want to take the full distribution over labels into account.

Although research questions are the starting point in both disciplines, these are distinct. In the social sciences, tasks address more complex issues, e.g. correlating the coverage of protests with characteristics like event size and number of arrests during a political transition period (McCarthy et al., 2008), compared with identifying factuality in an article (Baly et al., 2018), detecting whether a sentence is biased or not (Lim et al., 2020; Lei et al., 2022; Spinde et al., 2021b), or categorising full news documents based on their framing about a specific issue (Naderi and Hirst, 2017; Ji and Smith, 2017; Khanehzar et al., 2019). Social scientists often consider external knowledge to draw conclusions. In contrast, most NLP work operates on the individual article level, disregarding external information as well as other articles in the collection. A few exceptions exist, including Baly et al. (2020) who incorporate readership demographics from Twitter and publisher information from Wikipedia; and Kulkarni et al. (2018) who incorporate article link structure into their models. Still, they consider each news item in isolation. We encourage the NLP community to ground frame predictions in external signals – be it document-extraneous (such as readership and sources) and/or cross-document (by explicitly contrasting the framing across articles from different times, locations, or outlets). We envision as a result more expressive frame conceptualizations; outputs and analyses that are more aligned with typical questions in the media sciences; and a stepping stone towards tools that can highlight contrastive framing of issues in the news to a general readership.

More broadly, we advocate for a more cross-disciplinary perspective in NLP research, involving domain experts in all steps of the process: from the formulation of research questions, to model design with consideration to transparency and robustness, and evaluation. While prior work has highlighted the importance of expert annotation (Spinde et al., 2021b), we argue that in order to develop useful assistive tools for scholars or applications for the general public, a dialogue with domain experts over the whole process is essential. Cross-disciplinary projects would guide NLP researchers to go back to the basics of framing analysis and political bias prediction as in the social sciences, and adopt back best practices in steps like annotation.

*What could NLP contribute to the social sciences?* NLP can support and scale up social science analyses with powerful tools like pre-trained and generative models accompanied with domain expertise on how to employ these tools safely and responsibly. For example, Bhatia et al. (2021) supply a web platform for semi-automatic data annotation and document classifier training in order to support communication-science researchers without the resources and skills in using automatic tools. The system generates LDA topics (Blei et al., 2003) in the first step and allows researchers to tag the topics and annotate documents, which are used as training data for document-level frame prediction.

NLP has a strong culture of sharing code and annotated data sets to encourage collaboration and reproducibility. This practice is less common in the humanities. Sharing this data more explicitly through cross-disciplinary dialogue could provide critical assessment and feedback from domain experts and encourage innovation on how to combine large (and potentially noisier) data into the small-scale (but high-quality) annotations, to address increasingly complex questions on the emergence and effects of media biases and framing.

## 6 Conclusion

This survey takes a critical look at recent work in NLP on framing and media bias, and points out disconnects and synergies in datasets, methodologies, and validation techniques to research practices in the social sciences. Despite the opportunities for

NLP to support and scale social science scholarship on media bias, a current oversimplification in conceptualisation, modelling, and evaluation models of framing and media bias hinders fertile collaboration. We have teased out three disconnects and proposed directions for future work, including: (1) analysing news articles from a local and global perspective, incorporating external non-textual features; (2) taking into account the dynamics of framing and bias across documents, cultures or over time; and (3) tackling the issue of media bias as a comparative task, defining frames on the basis of systematic differences between articles whose origins differ on pre-defined characteristics. This would allow for a more complex characterisation of bias than the currently dominant approach of single-label classification.

## Limitations

This survey focuses on framing to news articles. This constrains the scope of our analysis to media rather than framing in a broader context. Additionally, we are aware that regardless on the approach taken for sampling the previous work included in this manuscript, there will be always bias present. With the aim of mitigating this bias, we point the reader to complement our work with previous surveys in this field i.e. Hamborg et al. (2019) and Ali and Hassan (2022).

## Ethics Statement

Identifying framing and ideology bias in news articles is highly influenced by social and structural bias. Datasets and technologies intending to tackle these phenomena comprise the social bias of annotators and researchers developing them in an environment lacking diversity, in addition to the potential for dual use of models and benchmarks to promote polarisation and misinformation. However, we see this paper as an opportunity to identify new directions to diversify NLP methodologies and develop new datasets that help to push the field further, and address authentic analytical goals in the social sciences.

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