A Survey on Predicting the Factuality and the Bias of News Media

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Abstract

The present level of proliferation of fake, biased, and propagandistic content online has made it impossible to fact-check every single suspicious claim or article, either manually or automatically. Thus, many researchers are shifting their attention to higher granularity, aiming to profile entire news outlets, which makes it possible to detect likely “fake news” the moment it is published, by simply checking the reliability of its source. Source factuality is also an important element of systems for automatic fact-checking and “fake news” detection, as they need to assess the reliability of the evidence they retrieve online. Political bias detection, which in the Western political landscape is about predicting left-center-right bias, is an equally important topic, which has experienced a similar shift towards profiling entire news outlets. Moreover, there is a clear connection between the two, as highly biased media are less likely to be factual; yet, the two problems have been addressed separately. In this survey, we review the state of the art on media profiling for factuality and bias, arguing for the need to model them jointly. We further discuss interesting recent advances in using different information sources and modalities, which go beyond the text of the articles the target news outlet has published. Finally, we discuss current challenges and outline future research directions.

1 Introduction

The rise of the Web has made it possible for anybody to create a website or a blog and to become a news medium. This was a hugely positive development as it elevated freedom of expression to a whole new level, allowing anybody to have their voice heard. With the subsequent rise of social media, anybody could potentially reach out to a vast audience, some of them having their voice heard. With the subsequent rise of social media, expression to a whole new level, allowing anybody to have their voice heard. With the subsequent rise of social media, anybody could potentially reach out to a vast audience, some of them having their voice heard.

The issue became a general concern in 2016, a year marked by micro-targeted online disinformation and misinformation at an unprecedented scale, primarily in connection to Brexit and the US Presidential election. These developments gave rise to the term “fake news.”

Several initiatives, such as PolitiFact, Snopes, FactCheck, and Full Fact, have been launched to fact-check suspicious claims manually. However, given the scale of the proliferation of false information online, it became clear that it was unfeasible to fact-check every single suspicious claim, even when this was done automatically, not only for computational reasons but also due to timing. In order to fact-check a claim manually or automatically, we need to verify the stance of mainstream media concerning that claim and/or the reaction of users on social media. Accumulating this evidence takes time, and delay means more potential sharing of the malicious content. A study has shown that for some very viral claims, more than 50% of the sharing happens within the first ten minutes after posting the micro-post on social media [Zaman et al., 2014], and thus timing is of utmost importance. Moreover, an extensive recent study has found that “fake news” spreads six times faster and reaches much farther than real news [Vosoughi et al., 2018].

A much more promising alternative is to focus on the source and profile the medium that initially published the news article. The idea is that media that have published fake or biased content in the past are more likely to do so in the future. Thus, profiling media in advance makes it possible to detect likely “fake news” the moment it is published by simply checking the reliability of its source.

Estimating the reliability of a news medium source is important for tasks such as fact-checking a claim [Nguyen et al., 2020], and it also gives an important prior when solving article-level tasks such as “fake news” and click-bait detection.

There have been several surveys on “fake news” [Shu et al., 2017; Zhou and Zafarani, 2020; Cardos Durier da Silva et al., 2019], misleading information [Islam et al., 2020], fact-checking [Thorne and Vlachos, 2018; Kotonya and Toni, 2020], truth discovery [Li et al., 2016], and propaganda detection [Martino et al., 2020]. However, they have focused either on individual claims or on articles; in contrast, here we survey research on profiling entire news outlets for factuality and for

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bias.

2 Factuality

Veracity of information has been studied at different levels: (i) claim-level (e.g., fact-checking), (ii) article-level (e.g., "fake news" detection), (iii) user-level (e.g., hunting for trolls), and (iv) medium-level (e.g., source reliability estimation). Our primary interest here is in the latter.

At the claim-level, fact-checking and rumor detection have been primarily addressed using information extracted from social media, i.e., based on how users comment on the target claim [Castillo et al., 2011; Kochkina et al., 2018]. A set of web pages and snippets from search engines have also been used as a source of information [Karadzhov et al., 2017]. In either case, the most important information for the claim-level tasks are stance (does a tweet or a news article agree or disagree with the claim?) and source reliability (do we trust the user who posted the tweet or the medium that published the news article?).

The problem of source reliability remains largely under-explored. In the case of social media and community fora, it concerns modeling the user. In particular, there has been research on finding manipulation trolls, paid [Mihaylov et al., 2015a] or just perceived [Mihaylov et al., 2015b], sockpuppets [Maity et al., 2017], Internet water army [Chen et al., 2013], and seminar users [Darwish et al., 2017]. In the case of the Web, it is about the trustworthiness of the source (the URL domain, the medium). The latter is our focus here.

In early work, the source reliability of news media has often been estimated automatically based on the general stance of the target medium with respect to known true/false claims, without access to gold labels about the overall medium-level factuality of reporting [Mukherjee and Weikum, 2015].

More recent work has addressed the task as one on its own right. [Baly et al., 2018] used gold labels from Media Bias/Fact Check,¹ and a variety of information sources: articles published by the medium, what is said about it on Wikipedia, metadata from its Twitter profile, URL structure, and traffic information. In follow-up work, [Baly et al., 2019] used the same representation to jointly predict media factuality and bias on an ordinal scale, using a multi-task ordinal regression setup. Finally, [Baly et al., 2020b] extended the information sources to include Facebook followers and speech signals from the news medium’s channel on YouTube (if any). Finally, [Housel et al., 2020] proposed to use domain, certificate, and hosting information of the website infrastructure.

3 Bias

3.1 A Variety of Dimensions in Media Bias

Compared to factuality, which is decided by whether a piece of information is true or not, media bias has more complex dimensions. For the last few decades, many scholars have conceptualized media bias in different ways. For instance, a bias can be defined as “imbalance or inequality of coverage rather than as a departure from truth” [Stevenson et al., 1973]. They particularly note that a departure from truth, as a bias, can be measured only when the accurate record of the event is available (e.g., trial transcript).

A different definition, “Any systematic slant favoring one candidate or ideology over another” [Waldman and Devitt, 1998], is proposed to capture various other dimensions rather than coverage imbalance, such as favorability conveyed in visual representations (e.g., news photos). For example, smiling, speaking at the podium, cheering crowd, and eye-level shots are preferred over frowning, sitting, being alone, and shots from above, respectively.

D’Alessio and Allen reviewed 59 quantitative studies about partisan media bias in presidential elections [D’Alessio and Allen, 2000], and based on this analysis, they proposed to categorize media bias into the following three types: (i) gatekeeping bias, where editors and journalists ’select’ the stories to report, (ii) coverage bias, where the amount of news coverage (e.g., the length of newspapers articles, or the time given on television) each party receives is systematically biased to one party at the expense of the other one, and (iii) statement bias, where news media interject their attitudes or opinions in the news reporting. Groeling proposed a more relaxed concept of media bias, which is “a portrayal of reality that is significantly and systematically (not randomly) distorted,” to take a variety of media bias dimensions into account [Groeling, 2013]. In particular, he focused on two main forms of media bias—selection bias (i.e., what to cover) and presentation bias (i.e., how to cover it)—driven by the choices of newsmakers.

Selection bias or gatekeeping bias, has been studied in various ways, including qualitative interviews or surveys of journalists and editors about the decision making process they use to select the news stories in their newsroom [Tandoc Jr, 2014]. Data-driven research on selection bias follows the common steps: (i) collect news articles (for newspapers or online news) or transcripts (for television news) for a target period, (ii) conduct content analysis to find the news coverage of politicians, parties, events, etc. Sometimes the tone of the news articles can be studied (i.e., negative news stories are more frequently reported or selected by the editors compared to positive news) [Soroka, 2012], and (iii) identify systematic biases by comparing their news coverage. An exhaustive database of news stories is, thus, essential for selection bias research. While commercial databases, such as Lexis Nexis, have been widely used [Soroka, 2012], publicly available datasets, such as GDELT or Google News, start to get attention [Kwak et al., 2014; Boudemagh and Moise, 2017; Kwak et al., 2018] and are getting validated by comparing multiple sources [Weaver and Bimber, 2008; Kwak et al., 2016].

Presentation bias has been characterized from diverse perspectives, including framing [Entman, 2007], visuals [Barrett and Barrington, 2005], sources [Baum and Groeling, 2008], tone [Soroka, 2012], and more.
3.2 Framing Bias

Framing refers to a process that highlights a certain aspect of an event or an issue more than the others [Entman, 1993]. Emphasizing an issue’s particular aspect can deliver a distorted view toward the issue even without the use of biased expressions.

Framing biases have been typically studied at issue level. Researchers collect news articles about a particular issue or event, conduct manual content analysis on them, and build a frame detection model [Baumer et al., 2015]. Although this approach successfully characterizes diverse frames, it is not trivial to compare media’s framing across different issues.

The Media Frames Corpus (MFC) was proposed to address this limitation. It contains articles annotated with 15 generic frames (including others) across three policy issues [Card et al., 2015]. Several studies have demonstrated reasonable prediction performance of the general media frames with different datasets [Field et al., 2018; Kwak et al., 2020]. These 15 generic frames were also used for identifying frames in political discourse on social media [Johnson et al., 2017]. General media frames are often customized to a specific issue by adding issue-specific frames [Liu et al., 2019], even though doing so somewhat contradicts the original motivation of using general media frames, namely to be able to compare frames across various issues.

3.3 News Slant

As a related concept to framing, news slant was proposed to characterize how the framing in news reports favors one side over the other [Entman, 2007]. The media-level slant thus could be different across issues [Ganguly et al., 2020].

A variety of methods have been proposed to quantify the extent of news slant in traditional news media by (i) linking media outlets to politicians with known political positions, (ii) directly analyzing news content, and (iii) using shared audience among media outlets. For example, Groseclose and Milyo assigned an ADA (Americans for Democratic Action) score for each media outlet by investigating co-citations of think-tanks by members of Congress and media outlets [Groseclose and Milyo, 2005]. Genzkow and Shapiro proposed an ideological slant index of news media in a seminal study [Gentzkow and Shapiro, 2010]. The news slant is measured by the extent of phrases in news coverage that are more frequently used by one political party (i.e., Democratic or Republican) congress members than by another one in the 2005 Congress Record. Their frequency-based approach successfully finds politically charged phrases such as death tax or war on terror Republicans and associated media and estate tax or war in Iraq by Democrats and associated media, and they further computed media a slant index for 433 newspapers. The choice of words by political party members and news media can be considered framing as well because they purposely highlight some aspect of the issue over other ones. An et al. proposed a method to compute media slant scores by measuring distances between media sources by their mutual followers on Twitter and mapping them to a two dimensional space [An et al., 2011; Stefanov et al., 2020].

4 Basis of Prediction

4.1 Textual Content

Representation

The most natural representation for a source is as a sample of articles it has published, which in turn can be represented using linguistic features or as continuous representations.

Linguistic Features: These features focus on language use, and they have been shown to be useful for detecting fake articles, as well as for predicting the political bias and the factuality of reporting of news media [Horne et al., 2018; Baly et al., 2018]. For example, [Horne and Adali, 2017] showed that “fake news” pack a lot of information in the title (as many people do not read beyond the title, e.g., in social media), and use shorter, simpler, and repetitive content in the body (as writing fake information takes a lot of effort). Such features can be generated based on the Linguistic Inquiry and Word Count (LIWC) lexicon and used to distinguish articles from trusted sources vs. hoaxes vs. satire vs. propaganda [Pennebaker et al., 2001]. They can be also modeled using linguistic markers [Mihaylova et al., 2018] such as factives from [Hooper, 1975], assertives from [Hooper, 1975], implicatives from [Karttunen, 1971], hedges from [Hyland, 2005], Wiki-bias terms from [Recasens et al., 2013], subjectivity cues from [Riloff and Wiebe, 2003], and sentiment cues from [Liu et al., 2005]; see Table 1 for examples. There are 141 such features implemented in the NELA toolkit [Horne et al., 2018], grouped in the following categories:

- **Style**: part-of-speech tags, use of specific words (function words, pronouns, etc.), and features for clickbait title classification;

| Bias Type | Sample Cues |
|-----------|-------------|
| Factives  | realize, know, discover, learn |
| Implicatives | cause, manage, hesitate, neglect |
| Assertives | think, believe, imagine, guarantee |
| Hedges    | approximately, estimate, essentially |
| Report-verbs | argue, admit, confirm, express |
| Wiki-bias | capture, create, demand, follow |
| Modals    | can, must, will, shall |
| Negations | neither, without, against, never, none |
| Strong-subj | admire, afraid, agreeably, apologist |
| Weak-subj | abandon, adaptive, champ, consume |
| Positives | accurate, achievements, affirm |
| Negatives | abnormal, bankrupt, cheat, conflicts |

Table 1: Some cues for various bias types.
• **Complexity:** type-token ratio, readability, number of cognitive process words (identifying discrepancy, insight, certainty, etc.);
• **Bias:** features modeling bias using lexicons and subjectivity as calculated using pre-trained classifiers;
• **Affect:** sentiment scores from lexicons and full systems;
• **Morality:** features based on the Moral Foundation Theory [Graham et al., 2009] and lexicons;
• **Event:** features modeling time and location.

**Embedding representations:** An alternative way to represent an article is to use embedding representations, typically based on BERT [Devlin et al., 2019]. This can be done without fine-tuning, e.g., by encoding an article (possibly truncated, e.g., BERT can take up to 512 tokens as an input) and then averaging the word representations extracted from the second-to-last layer. Alternatively, one can use pre-trained sentence encoders such as Sentence-BERT [Reimers and Gurevych, 2019] or the Universal Sentence Encoder (USE) [Cer et al., 2018]. Finally, one can obtain representations that are relevant to the target task, e.g., by fine-tuning BERT to predict the label (bias or factuality) of the medium that an article comes from, in the form of distant supervision [Baly et al., 2020b]. One issue with distant supervision is that the model can end up learning to detect the source of the target news article instead of predicting its factuality/bias, which can be fixed using adversarial media adaptation and a specially adapted triplet loss [Baly et al., 2020a].

**Aggregation**

In order to obtain a representation/prediction for an entire medium, there is a need to aggregate the representations/predictions for its articles.

**Averaging article-level representations:** One could average the representations for all articles to obtain a representation for a medium, which can then be used to train a medium-level classifier. Using arithmetic averaging is a good idea as it captures the general trend of articles in a medium, while limiting the impact of outliers. For instance, if a medium is known to align with left-wing ideology, this should not change if it published a few articles that align with right-wing ideology.

**Aggregating posterior probabilities:** Alternatively, each article can be represented by a C-dimensional vector that corresponds to its posterior probabilities of belonging to each class \( c_i, i \in \{1, \ldots, C\} \) of the given task, whether it is predicting the political bias or the factuality of the target news medium. Finally, these article-level posterior probabilities are averaged in order to aggregate them at the medium level.

### 4.2 Multimedia Content

We have come to understand events in a far more visual way than we have ever before. As a result, multimedia content is now heavily relied upon as a source of news and opinion and has been an important element of almost all news websites. This dependence, however, also makes multimedia a very effective means for dispensing an intended, and even manipulated, message. The increasing availability of automated and AI-powered multimedia editing and synthesis tools, combined with massive computational power, makes such capabilities accessible to everyone.

Given that multimedia editors of a news site typically follow a defined workflow when creating, acquiring, editing, and curating content for their pages, this pattern thus adds a crucial dimension to profiling the factuality and the bias of a news source. In fact, questions around the origin and the veracity of photographic images and videos have long been the subject of multimedia forensics research [Sencar et al., 2013].

With this objective, several methods have been proposed based on verifying metadata integrity [Iuliani et al., 2018; Yang et al., 2020], digital integrity [Cozzolino et al., 2018], physical integrity [Uuliani et al., 2017; Matern et al., 2020], identification of processing traces [Hadwiger et al., 2019], and discrimination of synthesized (i.e., GAN generated) media [Agarwal et al., 2020; Verdoliva, 2020]. Currently, these capabilities have only been sparsely explored in the context of predicting factuality and bias.

Existing work mainly considered characterization of images appearing at trustworthy sources and such obtained from low-factuality news sources. These methods have proposed to use visual characteristics of images [Jin et al., 2016], deep-learning visual representations [Qi et al., 2019; Singhal et al., 2019], image provenance information obtained through reverse image search [Zlatkova et al., 2019], and self-consistency with respect to metadata information [Huh et al., 2018]. Overall, the results of this line of research indicate that multimedia characteristics have a strong potential that has not yet been fully used for news media profiling.

### 4.3 Audience Homophily

The well-known homophily principle, “birds of a feather flock together,” crucially asserts that similar individuals interact with each other at a higher rate than dissimilar ones. Therefore, audience representation could be another approach to describe a news media outlet whereby an overall, descriptive characteristic of followers of the outlet is obtained. Then, by evaluating the similarity of audience-centric representations with previously categorized news media, the factuality and the bias of the medium in question can be inferred.

[Ribeiro et al., 2018] used Facebook’s targeted advertising tool to infer the ideological leaning of online media based on the political leaning of the users who interacted with these media, according to Facebook. [An et al., 2012] relied on follow relationships on Twitter to ascertain the ideological leaning of news media and users. [Wong et al., 2013] studied retweet behavior to infer the ideological leanings of online media sources and popular Twitter accounts. [Barberá, 2015] proposed a statistical model based on the follower relationships to media sources and Twitter personalities to estimate their ideological leaning.

[Stefanov et al., 2020] predicted the political leaning of media with respect to a topic by observing the users of which side of the debate on a polarizing topic were sharing content from which media in support of their position in the context of...
that debate. In particular, they constructed a user-media graph and then used label propagation and graph neural networks to derive representations for media, which they used for classification. They further aggregated the leanings across several polarizing topics to come up with a left-center-right polarization prediction.

Following a similar approach, [Baly et al., 2020b] considered three social media platforms for audience characterization. On Twitter, they proposed to use self-descriptions in publicly accessible profiles of users following the account of a medium. For each medium, a representation is obtained by encoding the biographic descriptions of Twitter followers and averaging the resulting textual representations. The second characterization involves how the audience of the medium’s YouTube channel responds to each video in terms of number of comments, views, likes and dislikes. By averaging these statistics over all videos, a medium-level representation is obtained. The last audience representation is obtained using Facebook’s advertising platform, which is used to obtain demographic information for the audience interested in each medium. This data is used to obtain the audience distribution over the political spectrum. The distribution is then divided into five categories to label each medium accordingly: very conservative, conservative, moderate, liberal, and very liberal.

4.4 Infrastructure Characteristics

Beyond textual, visual, and audience features, news sites also exhibit distinct characteristics that relate to the underlying infrastructure and technological components deployed to serve their content online. In this regard, the prediction problem is analogous to a well-studied one in the cybersecurity domain where the goal has been to identify infrastructure characteristics of malicious domains [Anderson et al., 2007; Invernizzi et al., 2014]. Since establishing the infrastructure of a news medium involves several decisions with respect to technological aspects, it is plausible to expect that news media with varying IT practices and different levels of access to IT human resources will differ in their characteristics.

So far, only a few works exploited this dimension with a focus on network, web design, and data elements of a news website to essentially discriminate new sites based on factuality and bias. At the network level, [Hounsel et al., 2020] considered a comprehensive set of features that relate to a website’s domain, certificate, and hosting properties. In a classification setting with three classes (i.e., disinformation websites, authentic websites, and sites not related to news or politics), their results showed that features related to a website’s domain name, registration, and DNS configuration serve as best predictors for classification. Concerning the web design aspect, [Castello et al., 2019] introduced a web page classifier based on several features that govern the structure and style of a page in addition to three categories of linguistic features. Their binary classification results (real or fake news) obtained on several datasets showed that the web-markup features consistently perform well and are complementary to linguistic features.

Lastly, at the data level, [Fairbanks et al., 2018] examined the source of web pages to identify shared data objects, such as mutually linked sites, scripts, and images, across web sites. This information is then used to create a shared data object graph. By comparing the content level features with the structural properties of the graph, they found that the use of mutually shared objects yields better performance in predicting both factuality and bias of a site with a significant difference in the former task. Overall, a major advantage of utilizing infrastructure features comes from their content- and audience-agnostic nature. Because of this, they allow making reliable predictions when only limited textual and visual content is available and without an established audience interest in a news medium.

5 Lessons Learned

Factuality and bias have some commonalities as they exert negative influences on the public by delivering information that is deviated from the truth. Not surprisingly, some news media purposely take a biased position in the political landscape and appeal to partisan audiences. This trend becomes apparent in recent years mainly because the news industry becomes more and more competitive. Many journalists and editors, however, have concerned about their biases in news selection and reporting and try to be neutral or at least report diverse perspectives of an issue.

As the bias can be conveyed in different means, which are text, photos, and videos, through even a very subtle way, the media bias has complex dimensions. Among them, ideological bias is an important conceptualization due to the importance of media bias in a political context. In the US context, the ideological bias could be broadly defined as conservative, center, and liberal. Then, the (ideological) bias prediction task is formulated as predicting whether a given news story, including both text and visual elements, favors one party over the other. Reported results so far show that accurate prediction of this ideological bias of a news medium is a far more easier task than assessing factuality. This is, in fact, not surprising as evaluation of the factuality ultimately depends on the authenticity and the objectivity of the particular claims stated in a news story, essentially requiring verification from other sources and observations.

Although more sophisticated analysis of the text style and multimedia characteristics may be expected to improve the achievable accuracy, it is evident that there is a big need to complement the textual and visual elements of a news medium with others. In this regard, recent studies have demonstrated the potential of audience homophily and the medium’s infrastructure characteristics in bridging the existing performance gap. The content-agnostic nature of these characteristics make them further useful in the early discovery and categorization of news media even in the absence of sufficient content.

6 Challenges and Future Forecasting

6.1 Major Challenges

Ordinal scales: While the ideological bias (news slant) is typically modeled as left-center-right, there exists a spectrum within each bias based on bias intensity. A hyperpartisan (an
extreme partisan) bias prediction task has been tested to differentiate far-right from right and far-left from left, but it does not model the political bias using an ordinal scale. Difficulties in labeling the bias (i.e., creating ground-truth datasets) by experts or crowdsourcing is a major hurdle for modeling ideological bias as an ordinal variable.

**Joint modeling:** There is a well-known connection between factuality and bias. For example, hyper-partisanship is often linked to low trustworthiness, e.g., appealing to emotions rather than sticking to the facts, while center media tend to be generally more impartial and trustworthy [Baly et al., 2019]. Thus, it makes sense to model factuality and bias jointly.

**Multimodality:** In news reporting, a news photo typically gets high attention from readers. The fact that readers sometimes can understand news stories from news photos only—even without reading text—indicates that news text and photos are strongly coupled together and deliver relevant information about news stories to readers. Thus, there should be a benefit from modeling news text and photos together to understand their bias and factuality.

**Evaluation granularity:** The label of a news medium is essentially inferred from a sample of observations. This potentially introduces a measurement bias when a news medium does not exhibit the same reporting behavior with all news items it publishes. This is especially the case for media that have a particular stance in only certain issues [Ganguly et al., 2020]. Thus, reliable estimation of factuality and bias labels require analyzing a relatively large amount of content covering a range of issues.

**Variability in factuality & bias ratings:** These ratings are inherently not static and may change over time when a news medium takes corrective action to address issues raised by fact-checkers. In other words, the ground truth needed for building a learning approach varies, triggering the need for re-evaluating the performance of proposed approaches. Therefore, there is also a need to take into account the sensitivity of a learning approach to such small but nevertheless inevitable variations.

**Dataset size:** The existing datasets for media-level factuality and bias are relatively small in size, typically of a few hundred examples, sometimes a few thousand. These are derived from sites, such as Media Bias/Fact Check and AllSides, where domain experts perform a careful manual analysis based on clear guidelines.

**Annotation vs. modeling:** One problem is that human annotators judge the factuality of reporting and the bias of media based on criteria that are not easy to automate or based on information that may not be accessible to automatic systems. For example, if a news outlet is judged to be of mixed factuality based on it having failed just 2-3 fact-checks, for an automatic system to arrive at the same conclusion using the same idea, it would have to select for analysis the exact same articles where the false claims were made.

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**Data availability:** Primarily due to copyright issues, there are only a few publicly available datasets of the full text of news for research purposes. Instead, indexed data (e.g., GDELT dataset4) by mentioned actors, events, locations, sources, or tones are available and have been analyzed in many studies. A set of news headlines collected from news websites or aggregated websites (e.g., AllSides5) are also shared more actively for research purposes. Considering the importance of social media channels in news dissemination, researchers collect and analyze social media posts of official accounts of news media. As social media posts are relatively more informal than news articles to fit for social media audience [Park et al., 2021], more studies are required for understanding their biases and factuality correctly.

### 6.2 Future Forecasting

Based on the challenges mentioned in the previous subsection, we forecast the emergence of the following research directions:

**Support for non-English corpora and different political systems:** Most of the studies we review are conducted based on English corpora. More research on bias and factuality in non-English corpora thus will be expected. Recently, various approaches are proposed to accelerate NLP research for resource-scarce languages, such as multilingual word embeddings. We believe that those efforts help conduct bias and factuality research for non-English corpora. One non-technical issue here is that not all the countries have US-like left-center-right political biases. For example, there might exist a multiparty system in some countries. In that case, understanding relevant political biases should be the first step in media bias research.

**Research on video news:** TV news accounts for significant portions of the news industry. Also, the presence of news media becomes strong in video-driven social media platforms over time. To get high user engagements, news media outlets upload short video clips curated for social media use, particularly on existing social media. Most previous studies on bias in video news have analyzed their transcripts instead of analyzing video directly. Commercial databases, such as Lexis Nexis, or open-source libraries to create subtitles are used to analyze news transcripts. We expect that more studies on analyzing video contents in an end-to-end manner will be presented to fully understand the bias and factuality of video news.

**Bringing practical implications:** Since the factuality and bias of news media largely influence the public, it is crucial to implement working systems so that readers can benefit from a rich stream of research. Several stand-alone websites, such as Media Bias/Fact Check, AllSides, and Tanbih [Zhang et al., 2019],6 aim to make media bias and factuality transparent to end-users, thus promoting media literacy. We expect new tools and services that support more media and languages in the coming years.

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4 [https://www.gdeltproject.org/](https://www.gdeltproject.org/)
5 [https://allsides.com/](https://allsides.com/)
6 [https://www.tanbih.org/](https://www.tanbih.org/)
7 Conclusion

We reviewed the state of the art on media profiling for factuality and bias, arguing for the need to model them jointly. We further discussed interesting recent advances in exploiting different information sources and different modalities, which go beyond the text of the articles the target news outlet has published. Finally, we discussed current challenges and outlined promising research directions.
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