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Digital News and the Consumption of Political Information

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The Internet has fundamentally changed how people access and use news. As Dutton and others (Chapter 13, this volume) note, there are concerns that the Internet leads us to get stuck in “echo chambers” or “filter bubbles”—limiting our access to points of view that might challenge our preexisting beliefs. This chapter introduces a network approach to analyzing news consumption in the digital age. The authors explain how we can compare patterns of news consumption across demographic groups, countries, and digital platforms, and determine if there are differences across groups of users and media systems. Measuring news consumption has long been difficult owing to the limitations of self-reported data, so this chapter is notable in offering a novel approach that leverages the digital traces that people leave behind when navigating the Web.

Digital technologies have caused a tectonic shift in how we obtain news. Mass media have given way to multiple forms of networked communication that offer access to personalized information, tailored to our individual preferences. The nature of the current media landscape is often encapsulated in analogies used recurrently: the image of a “balkanized” public space divided by “echo chambers,” for example, has been revived with newer metaphors, including “filter bubbles” and “algorithmic gatekeeping.” In this chapter, we present a strategy to move beyond metaphors and obtain metrics that can help us analyze patterns of news consumption as they change across national contexts, demographic groups, and digital platforms. Our focus is on audience behavior and, in particular, on how much overlap news sources have in the

audiences they share. We use that overlap to build audience networks that allow us to determine the strength of fragmentation in news consumption.

The analysis of how people consume news, or whether certain groups differ in their news consumption habits, is important in understanding a core mechanism of democratic engagement. However, to offer such an analysis we need first to answer the following questions: How can we analyze patterns of news consumption in a way that can be compared across demographic groups, countries, and digital platforms? How can we measure the extent of fragmentation in those patterns? This chapter introduces an analytical approach that allows us to answer these questions. The approach involves analyzing the similarity of news sources in terms of the audiences they share: if two news sources share a lot of readers, our approach assigns them a strong connection in a network of audience overlap. In this digital age, “readership” or “audiences” can mean very different things—from individual subscriptions requiring a fee to the more improvised browsing, following, or sharing of news that the Web and social media allow in myriad ways. Depending on how we define “readership,” the interpretation of the connection between individuals and news sources will necessarily change but, in essence, it always taps into the same process: selective exposure to news and political information.

Digital technologies have multiplied the number of news sources available for consumption, but, crucially, they have also made it easier to analyze how that consumption takes place using observational data. In the past, most research on exposure to news relied on self-reported measures collected through surveys. Although many interesting trends have been uncovered using survey data, it is also well known that the approach has many limitations, mostly derived from measurement issues associated to imperfect recall (Prior, 2007). The approach we describe here relies on digital traces that tell us the number of people that accessed a given news website or that retweeted a given news link. Our approach, in other words, relies on actual traffic to news sources (or volume of engagement) and then asks how many unique users who access a given source also access a second source. This measure of overlap allows us to build the audience networks that we then analyze to compare patterns of news consumption across groups, countries, or platforms. These networks also help us map the different possible configurations that characterize media landscapes and, in particular, how well positioned digital-born media (i.e., media with no offline edition) are compared to more traditional legacy brands (i.e., those that originated in print or broadcasting).

The media ecology has been drastically reconfigured by the irruption of new actors, like digital-born outlets, news aggregators, or blogs (Carlson, 2007, 2017; Lewis, 2012; Singer, 2003). In countries as diverse as France, Mexico, Spain, or the US, for instance, some of these new actors (i.e., BuzzFeed, the

Huffington Post) have been able to build comparable audiences to those of legacy news providers (i.e., traditional newspapers, see Barthel, 2018). However, overall legacy organizations are still very prominent providers of news and political information. Determining the role that digital-born media play vis-à-vis more traditional news organizations requires empirical investigation—for instance, to test the hypothesis that new actors are attracting traffic away from legacy brands, or that they are becoming more prominent amongst the younger cohorts. The analytical approach we discuss in this chapter can be used to test such hypotheses: it provides quantifiable evidence of the position that different news outlets have in the media landscape, and whether that position changes across demographic groups or digital platforms. As we explain later in the chapter, the construction of networks of audience overlap can determine if specific types of outlets (say, digital-born) are more central, overall, than legacy brands.

The rest of the chapter proceeds as follows: first, we offer a brief overview of the forces that have prompted a change in the media landscape—a change that, according to many accounts, has increased the levels of fragmentation in the consumption of news. Then, we introduce the main building block of our methodology: a measure of audience overlap between news sources. This measure can be operationalized in different ways, depending on the data source or platform under analysis. In the section entitled “How to Build Audience Networks,” we explain how this measure allows us to build audience networks that provide the raw material for the rest of the analysis. The section following this discusses how these networks can be analyzed, and how those analyses provide measures that can be compared across political contexts, demographic groups, or platforms. We conclude with a discussion in which we assess the role of methods and measurement for theory building.

The Changing Media Landscape

Internet technologies have dramatically changed patterns of news consumption and reshaped how people keep up with current events. In a way, these changes are not entirely new: the television also brought a major shift in how people consume news, and before that, the radio radically changed access to news compared with the newspaper era (Katz, 1996). What characterizes the current era, however, is the sheer number of new sources that are available at the touch of a finger. This explosion of news sources derives, mostly, from the lowered costs of distributing information over the Web (Bimber, 2003).

The Web and social media have increased the number of actors providing news on the supply side; crucially, digital technologies have also reallocated

the levels of reach and influence amongst those actors. Publishers that traditionally controlled the means of production and distribution of information have seen their position challenged by the irruption of digital-born outlets that have been very successful in building audiences—in some cases building an audience as large as that of legacy media, especially in countries where traditional publishers are weak or do not generate much trust (Barthel, 2018; Majó-Vázquez, Zhao, and Nielsen, 2017; Nicholls, Shabbir, and Nielsen, 2016; Willsher, 2018). Digital-born outlets, in other words, have become increasingly influential in reaching (and potentially influencing) readers.

Social-media platforms have also secured much of the power that in the past was exclusively in the hands of legacy publishers. By controlling a large portion of the news distribution process, social-media platforms have drastically reconfigured the online news domain. Today, more people get news via Facebook than via any single news organization (Newman, Fletcher, Kalogeropoulos, Levy, and Nielsen, 2017). Social-media platforms increasingly mediate the relationship between readers and publishers (Bialik and Matsa, 2017) and, therefore, have the power to largely change the dynamics of news consumption (Nielsen and Ganter, 2017; Moore and Tambini, 2018). In 2018, Facebook downgraded news to favor posts from friends and family by changing the algorithm that ranks content (Mosseri, 2018). This strategy is intended to reduce the impact of “fake” news but might, in fact, be amplifying the biases embedded in social networks, for example, the tendency that people have to be connected to those who think similarly, enclosing them in ideological “echo chambers.”

In parallel, all these changes have also had an impact on the demand side of the news domain. Much of what we know about news consumption and audience attention under the mass media paradigm needs to be revisited (Ognyanova, 2018; Prior, 2007). Digital technologies have prompted a transition from the days when entire nations gathered around the same televised broadcast to a more fragmented public that has access to a high number of alternative sources for news. Metaphors like “echo chambers” and “filter bubbles” have flourished to describe this new scenario in which like-minded individuals consume news only from the set of outlets that matches their interests and beliefs (Pariser, 2011; Sunstein, 2009; Turow, 1998). These dynamics are reinforced by the algorithms that social-media platforms employ to magnify social signals received from friends—who are likely to share similar attitudes and viewpoints (Bakshy, Messing, and Adamic, 2015).

It remains an empirical question, however, whether news consumption can be characterized by fragmentation. Likewise, empirical evidence is necessary to illuminate whether the extent of fragmentation differs across political contexts, demographic groups, and platforms. These two questions lie at the heart of an open debate in the literature (Anderson, 2006; Dubois and Blank,

2018; Fletcher and Nielsen, 2017; Majó-Vázquez, Nielsen, and González-Bailón, 2018; Majó-Vázquez, Cardenal, and González-Bailón, 2017; Mukerjee, Majó-Vázquez, and González-Bailón, 2018a; Webster, 2008; Webster and Ksiazek, 2012). Our goal in this chapter is to show how computational tools can contribute to this debate. The main advantage is that they can shed new, comparative light on empirical trends using digital trace data, which produces more accurate results than the self-reported data employed in the past and collected with survey measurement instruments. Our approach borrows tools from network science and harnesses the potential of digital trails. In particular, it employs a measure of audience overlap across news sources to build networks that reveal the hidden structure of news consumption at the population level.

Audience Overlap and Why it Matters

Audience overlap measures how many people two media outlets share. The use of audience overlap metrics has a relatively long history in media research, going back to the sixties, when researchers started measuring shared public among media entities—mostly TV channels or programs—for the advertising industry (Goodhardt and Ehrenberg, 1969; Goodhardt, Ehrenberg, and Collins, 1987). The use of audience overlap data to map networks connecting media outlets has already generated a long stream of research (e.g., Ksiazek, 2011; Webster and Ksiazek, 2012; Taneja and Wu, 2014; Taneja, 2016; Taneja and Webster, 2016; Majó-Vázquez, Cardenal, and González-Bailón, 2017; Majó-Vázquez, Nielsen, and González-Bailón, 2018a; Mukerjee, Majó-Vázquez, and González-Bailón, 2018a; Mukerjee, Majó-Vázquez, and González-Bailón, 2018b). In this chapter, we follow those methodological developments and discuss the theoretical implications.

Audience overlap data offers important insights on how audiences navigate the many news sources that are available in online environments. First, audience overlap can be interpreted as a measure of similarity: the more consumers any two news sources share, the closer those sources are in terms of their audience base. Second, audience overlap can also be used to approximate the diversity of people consuming a given news outlet. For example, in Figure 14.1, nodes represent news outlets (e.g., the *New York Times*, the *Washington Post*, BuzzFeed) and the ties measure overlap. If outlet X has strong overlap with eight other outlets (panel A), and outlet Y has strong overlap with only two others (panel B), we can infer that outlet X attracts people with a wider range of interests than outlet Y. When this assessment is made for all news outlets, we can build a network, as the rest of the chapter explains, where the ties tell us how much overlap any two news sources have but also,

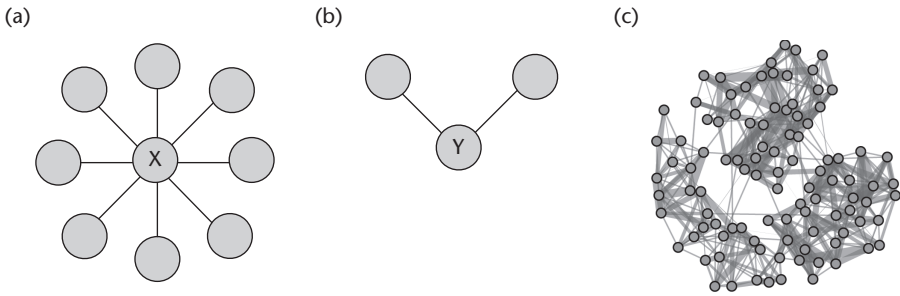


Figure 14.1. Illustrative examples of networks of audience overlap

and crucially, whether audiences self-select (or cluster) around specific outlets. In the schematic figure given in Figure 14.1C, for instance, there are three clusters in which news sources have denser internal overlap. This aggregated pattern suggests evidence of selective exposure at the individual level: some individuals are more likely to consume a set of outlets than others, resulting in fragmentation (as depicted by the clusters). Crucially, fragmentation in the context of this analytical framework goes beyond the number of news sources available for consumption (which is, trivially, much higher today than in the broadcast era); our approach measures, instead, the ways in which audiences converge or diverge around information sources.

An additional consideration of this approach is that the strength of the overlap is an important element in the analyses. The overlapping ties in Figure 14.1C, for example, differ in thickness; the reason is that the amount of audience any two news sources share can vary drastically. As mentioned, some news sources are more similar than others in the readers or consumers they attract (and they are thus connected by stronger ties). Of course, the strength of these ties will also depend on the total reach of news sources: those with higher audience reach will have more overlapping ties with other outlets just because they have a larger audience base. And yet, again, two outlets with the same total reach might have very different positions in the overall network—for instance, they might belong to different clusters. The only way to find out how news outlets compare with one another, and determine the strength of the fragmentation in the overall news consumption network, is by reconstructing these networks with empirical data, a goal that we illustrate in the following section.

How to Build Audience Networks

The first step in building audience networks is defining the boundaries of the network, or in other words, identifying the list of news outlets that should be

included as nodes. The second step is defining audience overlap—which, in this digital age, can be operationalized in different ways. For example, in the context of web browsing, “audience overlap” refers to the number of users who access two news sites within a given time period. If, instead, we are analyzing news consumption in social media, such as Twitter or Facebook, we can define overlap as the number of users who share links published by two news outlets: in this case, the measure taps into active engagement with specific news; with web browsing, on the other hand, we are only measuring the consumption of news content in general. It is important to note that in both cases we are measuring the number of people who get exposed to content produced by news sources, but the measures tap into different levels of engagement or responsiveness to the news. One additional possibility with social-media data is to use the number of followers that a pair of news outlets shares: when users choose which outlets they follow, they express their preferences for some outlets over others.

However we measure audience overlap, the underlying data structure is very similar: a matrix that converts those measures into a network. Figure 14.2 illustrates this data structure using a measure of audience overlap drawn from Web browsing behavior in the UK. For the sake of clarity, this example focuses on a small subset of all news sources that are available to Web users. The data provider, a media analytics company, uses representative panels of Internet users to draw estimates of audience reach and audience overlap (for a lengthier discussion of the data, see Mukerjee, Majó-Vázquez, et al., 2018). Every cell in the matrix reproduced in panel A contains the estimated number of Internet users who accessed a given pair of websites during the months surrounding the 2016 Brexit referendum (the numbers are expressed as thousands). Note that the matrix is symmetrical: the upper and lower triangles contain the same information, which translates into the undirected network reproduced in panel B. The size of the labels in this network is proportional to the total audience reach of the corresponding websites. The thickness of the ties is proportional to the overlap connecting pairs of websites (i.e., the cell values in the matrix).

If we wanted to map news consumption in social media, the contents of the matrix would derive from alternative measurements like those just mentioned, that is, number of links published by two news outlets that are shared by the same people, or overlap in the number of followers. Likewise, the same data structure can capture audience overlap through nondigital channels, for example, audience shared between television news programs. These alternative forms of measuring news consumption (or exposure to news content) will lead to slightly different interpretations of the networks; but the analysis of those networks always follows the same logic, as the following section explains.

(a)

	bbc	breitbart	buzzfeed	huffingtonpost	independent	mirror	newstatesman	newsweek	spectator	telegraph	dailybeast	economist	guardian	sun
bbc		184	1526	868	3872	3829	282	171	469	6099	175	514	6401	1713
breitbart	184		45	50	122	103	16	10	43	149	17	32	145	85
buzzfeed	1526	45		164	723	711	81	37	86	926	48	128	978	380
huffingtonpost	868	50	164		426	415	72	38	117	387	35	76	505	204
independent	3872	122	723	426		1809	186	93	279	2579	109	310	2545	679
mirror	3829	103	711	415	1809		159	114	154	2396	99	235	2087	1093
newstatesman	282	16	81	72	186	159		15	44	199	14	38	227	71
newsweek	171	10	37	38	93	114	15		25	157	7	19	117	30
spectator	469	43	86	117	279	154	44	25		389	20	65	348	124
telegraph	6099	149	926	387	2579	2396	199	157	389		132	348	3847	1003
dailybeast	175	17	48	35	109	99	14	7	20	132		11	140	56
economist	514	32	128	76	310	235	38	19	69	384	11		397	54
guardian	6401	145	978	505	2545	2087	227	117	348	3487	140	397		950
sun	1713	85	380	204	679	1093	71	30	124	1003	56	54	950	

(b)

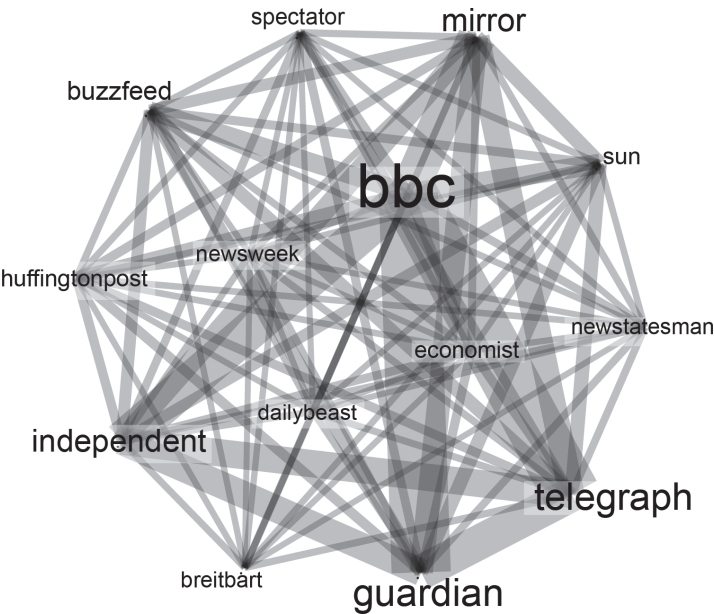


Figure 14.2. Matrix and graph representation of audience overlap (May–July 2016)

How to Analyze Audience Networks

Once we have encoded audience behavior in the form of a network, the next step is to analyze that network to summarize what it reveals about news consumption. One conclusion we can draw from Figure 14.1B, for example, is that the network is very dense, that is, most news sources share audience with most other news sources. Of course, the strength of the overlap also changes drastically across pairs, partly because the total audience reach of these sources is heavily skewed, that is, sites like *bbc.com* attract many more users than smaller sites like *thedailybeast.com*. One way to determine where most of the news consumption takes place is by eliminating the weakest overlapping ties. This procedure is known in the networks literature as thresholding (Borge-Holthoefer and Gonzalez-Bailon, 2015). Figure 14.3 shows the network at two levels of thresholding, one more stringent (panel C) than the other (panel B).

By eliminating the weakest ties, the core of the network is more clearly exposed. In our example, this core is formed mostly by legacy media brands. It is also clear, however, that digital-born outlets such as the *Huffington Post* or BuzzFeed have a comparable position to the long-standing tabloid the *Sun*—their audience reach is, in fact, more or less equivalent. All three of them lag behind the more established brands like the *Guardian* or the *Independent*. Because of the disparities in audience reach, it is important to have a baseline to determine what counts as significant overlap, that is, as a significant departure from randomness—taking into account that these sources are very different in audience reach to begin with. There are two approaches that have been used in the literature with this purpose: one determines statistical significance on the dyadic or pair level using the *phi* correlation (Fletcher and Nielsen, 2017; Majó-Vázquez et al., 2017; Mukerjee et al., 2018a), and the second uses a node-level filter that is known as backbone extraction (Majó-Vázquez et al., 2018).

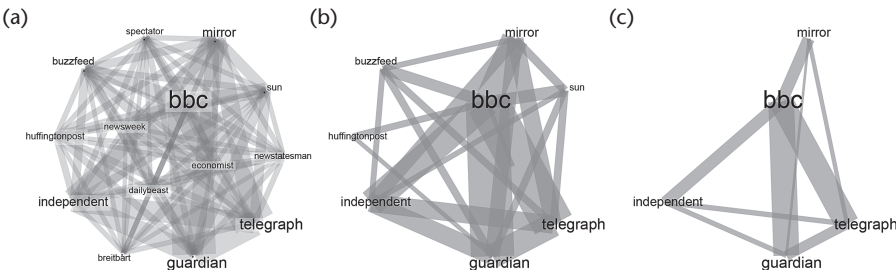


Figure 14.3. Audience overlap network before and after thresholding

In addition to the use of tie weights (or the strength of the overlap) to get a better sense of the network, there are other statistics that can help us summarize its structure—and provide metrics to engage in comparative research. In general, networks can be analyzed from three different levels (Borgatti, Everett, and Johnson, 2013; Newman, 2010). At the micro-level we look at the individual properties of nodes; for instance, their centrality scores. The sites at the core of our example network are more central than the sites at the periphery because they share audience with a wider range of news outlets. At the macro level, we shift focus to the distribution of those node-level features; for instance, we might be interested in the shape of the distribution of centrality, or how skewed that distribution is. Finally, between these two levels we have the meso scale, from where we identify clusters or groups of nodes. In the example we are considering here, the observed network looks very different from the hypothetical scenario depicted in Figure 14.1C; the empirical data we consider here does not offer much evidence of fragmentation.

Of course, the relevant question is whether this absence of fragmentation remains across platforms (i.e., maybe there is stronger evidence of self-selection in social media) or across political contexts (i.e., the UK has stronger public service media than the US, which leads to less fragmentation). Research in this direction is still incipient, but the first findings suggest that there are identifiable differences in how audiences consume news depending on the political context and the regulatory frameworks that shape that consumption (Majó-Vázquez et al., 2018a). The ability to measure those differences is important because they offer quantifiable evidence that relativizes the disruptive role of digital technologies when it comes to granting access to news: technologies are the same everywhere, but the level of centrality or fragmentation, or the popularity of digital-born outlets vis-à-vis legacy brands varies depending on the regulatory frameworks, journalistic practices, and levels of media trust in which news outlets operate.

Discussion: Measurement and Theory

In this chapter we have introduced an analytical approach that allows us to analyze news consumption in the form of networks of audience overlap. In these networks, nodes are news sources connected through shared audiences. The analysis of these networks offers a standardized language and metrics with which to compare news consumption patterns across platforms, countries, or demographic groups. The way in which we operationalize audience overlap differs across technologies (i.e., Web users access news domains, social-media users share news links), but since the network composition is the

same across them all (i.e., news sources that have a website tend also to have social media profiles), we can compare how similar the networks are depending on the platform through which news is being accessed. The same applies to different demographic groups.

Empirical research benefits greatly from the development of new methods and metrics with which to uncover patterns. Most of past scholarship on the impact that digital technologies have on news consumption makes bold empirical claims about increasing fragmentation. The type of analyses we have introduced in this chapter can help us contextualize those claims in a frame of comparative research. The prevalence and reach of digital-born outlets, for instance, can vary drastically from country to country—and so can the strength of the evidence consistent with audience self-selection. In the simplified example we have used in this chapter (simplified because we have focused attention on a small subset of news outlets to enhance clarity), we do not find evidence that audiences are segregated around different sets of outlets. However, as research has started to show, the evidence might be stronger in other political contexts. Accumulating evidence on these patterns and, more generally, on how digital technologies shape access to news is important in understanding a core mechanism of democratic engagement. The quality of democracies, in the end, depends on the ability of citizens to stay informed.

Being able to access the appropriate data is, of course, a necessary condition for the approach introduced here to work. The great research advantage associated with digital technologies is that they generate observational trails; the great disadvantage is that those trails are often proprietary. Some of that data can be accessed through commercial agreements with media measurement companies (like the data analyzed in this chapter), but some other trails are impossible to obtain for a mixture of privacy and corporate reasons: only researchers working for those corporations can analyze the data, and they have a difficult-to-elude conflict of interest.

All in all, however, the approach we have discussed in this chapter is a step forward in our understanding of news consumption, if only because it demands greater conceptual clarity about what we mean by fragmentation. It is obvious that we now have many more news sources that were available in the past; it is less obvious that such an enlarged supply inevitably results in higher audience self-selection, or that the effects are the same across media environments or political contexts. This line of research capitalizes on past work to formulate new questions about how to best measure audience behavior and exposure to news—and how to best use those measures to offer a more comprehensive understanding of how people stay informed of political affairs. This chapter offers just an entry point to what is an exciting and ongoing line of research.

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