Ognyanova, K. (2017). Multistep flow of communication: Network effects. In P. Roessler, C. Hoffner, & L. van Zoonen (Eds.), The International Encyclopedia of Media Effects (pp. 1-10). New York, NY: Wiley-Blackwell.

Multistep Flow of Communication: Network Effects

Katherine Ognyanova

Rutgers University

katherine@ognyanova.net

Word Count (not including abstract): 3958

Abstract

The multistep flow paradigm describes the way media and interpersonal influence shape public opinion. Works in that tradition explore the diffusion of media messages and the complex patterns of behavioral contagion in social networks. The flows of influence and information are amplified by opinion leaders: key individuals who can change the beliefs and actions of others in their community. Sociometric approaches provide a way to identify influencers based on their structural position or ability to trigger information cascades. Advances in network methodology allow us to model diffusion processes and study the interplay between interpersonal ties and individual behavior.

Multistep Flow of Communication: Network Effects

The multistep paradigm emerged as an extension of the *two-step flow* theory (Katz & Lazarsfeld, 1955), an important research tradition exploring the interplay of interpersonal and mass communication. According to the two-step model, direct media effects are hampered by social interactions and audience selectivity in exposure, perception and retention. Rather than reaching the public directly, ideas broadcasted by news outlets are channeled through a particularly active audience segment known as the *opinion leaders*. Those key individuals would receive, interpret, and disseminate media messages among the larger public.

In the decades after its inception, the two-step flow theory went through a number of modifications. The framework was criticized for underestimating the direct effect of mass communication (Robinson, 1976), especially as the Internet and mobile devices provided ubiquitous direct access to media content (Bennett & Manheim, 2006). Scholars have also suggested that the linear top-down model proposed by the Lazarsfeld and Katz oversimplified patterns of interpersonal influence. The flow of ideas from mass media to individuals was found to be more complex than the theory predicted. Key dynamics missing from the original model included the information exchange among opinion leaders, as well as that among the less engaged audience members (Weimann, 1982). The effects also did not disappear after two steps – the opinion leaders could convey ideas to followers who in turn would spread those ideas to other individuals. New models featured complex patterns of multidirectional flow allowing for bottom-up impact of audiences on media coverage (Brosius & Weimann, 1996).

Diffusion and social contagion

Research exploring the flow of ideas in social groups requires a holistic analytical perspective that incorporates individual characteristics, dyadic relations, and system-level processes. Network models of influence and diffusion provide a natural extension to the multistep flow paradigm.

Diffusion studies track the spread of ideas, conventions, or technologies through a social network. Works in this area explore the factors that promote or hinder the propagation of information, practices, and products. This research tradition does sometimes examine the role of influencers, but it is more concerned with the characteristics of innovators and early adopters (Rogers, 1995). Although those categories have been conflated by some authors, in a network context they are quite distinct. Opinion leaders are typically well-embedded in the social structure, highly connected, and very visible. In order to retain their central position, they have to follow community conventions and cannot deviate too much from the accepted norms. Trying new things, however, is easier when social control is weaker. Innovation comes from the edges, which is why early adopters are often found at the periphery of social systems.

The propagation of information and opinions can be presented analytically using *threshold* and *cascade* models. In threshold models, an individual adopts a behavior or opinion only after a certain proportion of their social ties have already adopted it. In a cascade model, each time a person is "infected" with a new opinion or information, there is a certain probability that the infection will spread to their connections. Adapting models from epidemiology, researchers have used the SIR (Susceptible - Infected - Recovered) cycle to describe *social contagion*. Individuals are considered susceptible when they are exposed to certain information (for instance a newspaper story), infectious while they talk about it to others, and recovered once they stop propagating it.

Network interpretations of the multistep flow

Network research in the multistep flow tradition falls into one of two categories (Ognyanova & Monge, 2013). The first investigates social structure as a conduit for the spread of ideas and information. The focus in that context is on individuals and the connections among them (including, among others, ties of friendship, kinship, collaboration, discussion, advice – as well as their online equivalents). Media outlets are not seen as part of this network, though they do produce the content that propagates through it. The work of Menzel and Katz (1955) provides one canonical example of this type. Their research mapping the social ties of health professionals finds a multistep influence of medical journals and interpersonal relations on drug adoption.

In the second and more recent type of study, both individuals and media outlets are seen as embedded in a multidimensional network. As above, this model examines interpersonal ties, but it also incorporates connections to (and potentially among) specific media sources. Friemel (2015) for instance models the social networks of high-school students along with their connections to various TV programs. Interestingly, his analysis finds no evidence of opinion leadership in that context.

Many works in this second category allow for the possibility that individuals as well as media outlets can generate, selectively filter, and disseminate messages. Various network metrics (described in the next section) have been used to evaluate the relative influence of people and news sources in the system. This line of research has generated a number of studies exploring online influence patterns among news organizations and audiences, including research on opinion leadership on social media platforms (Xu, Sang, Blasiola, & Park, 2014).

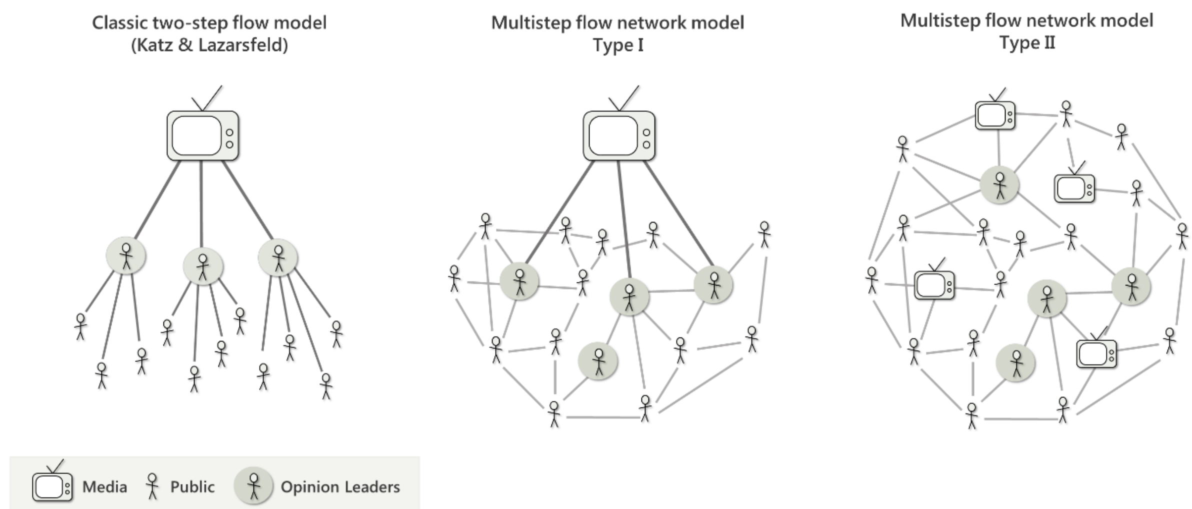

Figure 1. The two-step and the networked multistep flow models.

The sociometric profile of opinion leaders

Social influence refers to the notion that the people we know can affect our actions and attitudes. Substantive explanations for the emergence of interpersonal influence include patterns of persuasion, coercion, authority, identification, competition and expertise (Friedkin, 1998).

The *opinion leaders* are individuals who influence the attitudes, beliefs and actions of others. Their impact is domain-specific – the friends who can sway our political decisions may not be the same ones we go to for fashion advice or stock market tips. People in that position can inform, persuade, and manipulate others, as well as serve as role models and provide cues that signal the expected, acceptable or desirable behavior in a social group.

Since opinion leaders (also referred to as *influentials*) emerge in a variety of groups and contexts, they are not known to have specific socio-demographic characteristics. One thing that they do have in common, according to the classic two-step flow theory, is their high exposure to media content.

Elaborating on the qualities of opinion leaders, Katz (1957) lists three major dimensions that differentiate influentials from the rest of the social group they belong to:

(1) Who one is – the individual characteristics and values of a person
(2) What one knows – the level of competence or expertise of a person
(3) Whom one knows – the person's accessibility and the connections they can mobilize. Broadly speaking, this reflects a person's position in their social network.

Research efforts seeking to identify opinion leaders have used a variety of measures and techniques that tap into one or more of these three dimensions. Some approaches rely on self-reported data collected by asking people to rate their own influence, or administering more sophisticated survey scales. Other techniques are based on nominations from domain experts or community members. Influencers can be selected because of their prominent role in a group (as formal leaders, elected officials, media representatives, etc.), or identified by trained researchers through observational methods.

Taking a network perspective to the theoretical framework, researchers have also evaluated opinion leadership through sociometric techniques. Depending on the goals and the resources of the study, one of several standard data collection strategies may be used:

- **Full networks**: used when the researchers have access to a whole population forming a well-defined community (e.g. doctors in a hospital, students in a school, employees in an organization). Every individual is asked to describe their social ties with others in this group. Combining the individual reports allows researchers to map the entire network of the focal community.
- **Personal (ego) networks**: used when the population under study is too large to feasibly map with the available resources (e.g. all citizens of a country), or when it is difficult to identify all members of the group. In those cases, a random sample of respondents can be selected. Each participant (here called *ego*) is asked to describe their social ties with others (called *alters*) who may not be in the sample. The combined reports do not form one global network for the sample, but describe the local social structure of each respondent.
- **Snowball networks**: used when the full population is unknown, especially with difficult to reach or at-risk groups (e.g. drug users, HIV positive people). A sample of respondents is selected and each is asked to identify their social ties. At the next step, researchers contact those connections and collect information about their social ties too. The process can be repeated until a sufficient portion of the network is reached. This technique is expensive in terms of both time and resources. Because of that, in practice snowball samples rarely go more than two or three steps out from the initial set of participants.
- **Online networks**: While the previous paragraphs describe traditional data collection strategies, much of the cutting-edge research in the area has moved into the realm of online influence. Web platforms like Facebook and Twitter facilitate the collection of very large digital-trace sociometric datasets. Those provide a way to reconstruct full networks describing various online relations (e.g. social media ties of *following*, *friending*, *sharing*, *liking*) among millions of people. In addition to link structure, those datasets often contain records showing exactly when, how, and what media content spread through the network.

It is important to note once again that the set of opinion leaders identified through network analysis will largely depend on the social ties one chooses to study. Different patterns of influence will emerge in networks generated by asking "Who do you talk to about politics?", "Who do you go to for financial advice?", or "Whose fashion-related tweets do you retweet?".

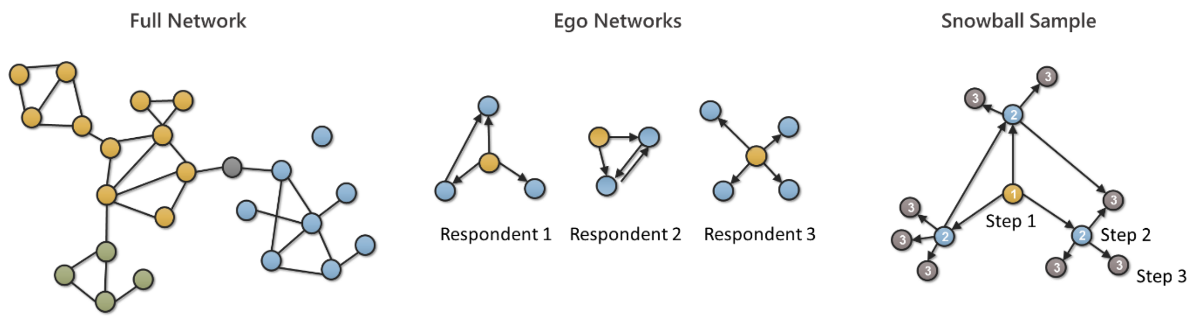

Figure 2. Network data collection strategies.

Network-based measures of personal influence

A common approach to identifying influencers based on sociometric data is through measures of network centrality. One way to quantify power in networks is based on the overall number of social connections a person has (known as *degree centrality*). Well-connected individuals tend to be prominent, popular, and have access to information and resources. In directed networks (such as advice-seeking), having a large number of incoming ties may signal high status or expert knowledge.

Some forms of centrality take into account not only direct, but also indirect connections to other members of the social network. If an individual can easily reach everyone else in their community (either directly or going through a small number of intermediaries) they have high *closeness centrality*. People with easy access to everyone in the network may be particularly effective in spreading and gathering information.

Another way to think about structural influence relies on identifying people who hold brokering positions. Individuals who bridge different parts of a network have high *betweenness centrality*. This measure is calculated by finding the shortest paths connecting any two people in the network, and counting how many of those paths pass through the focal person. In this context, brokers are individuals who connect otherwise disconnected social groups. In Ronald Burt's (1992) terminology, they are able to *span structural holes*. Being the only one (or one of the few) whose ties reach outside of the local community provides a number of advantages – such as having information or resources nobody else in the group can access. Brokers are, furthermore, strategically positioned to control the network flow. Occupying a bridging position enhances social capital and makes one more likely to be identified by peers as an opinion leader (Roch, 2005).

Some network position metrics are grounded in the idea that not all connections are equally important. One example, *eigenvector centrality*, is based on the premise that people may have more influence when their social ties are also highly influential. The score of an individual in this case is proportional to the combined scores of their alters. For instance, if two social media users have the same number of ties, the one whose contacts are more popular and well-connected would have a higher eigenvector centrality.

While centrality scores reflect structural characteristics, influence can also be measured through diffusion patterns. Instead of the total number of social contacts someone has, we can count the individuals whose opinion they have successfully changed, or the people they informed about a subject. Even more interesting, we can track cascades of influence going multiple steps out, beyond the immediate social environment of the person. This approach is used in a number of recent studies examining social contagion and information diffusion on social media and other digital platforms (Weng & Menczer, 2015).

Online platforms and influence flow

Over the last two decades, digital platforms have presented a wide range of new challenges and opportunities for research examining the flow of information and influence across individuals and media outlets. The Internet has increased the visibility of social structures and blurred the line between mass and personal communication. Social media provide a detailed record of interpersonal ties and exchanges among users. Online services facilitate and document the spread of news stories, as well as that of comments and interpretations supplied by audience members. Advances in network science and computational techniques have recently enabled the tracking and analysis of complex diffusion processes on the Web.

Studies exploring the multi-step flow of online communication have to account not only for shifts in user behavior, but also for changes in the observability and impact of individual actions in digital spaces. On a social media platform, audience members may encounter stories posted by news outlets they follow, or see links to news items shared by their friends. The platform, however, may also broadcast the actions of users who are not intentionally disseminating specific content. On the social network site Facebook, for instance, a person's information stream may contain stories that their social ties have liked or commented on. Activities of that kind (which may not have been observable in pre-Internet times) do not necessarily involve an intent to spread information to others.

The aggregated influence of individual decisions is also amplified in digital systems by the algorithms used to select and prioritize content. Online services often seek to highlight content that seems especially relevant or likely to elicit user engagement. To that end, they may display posts, images, links, or search results more prominently if those items have also been shared or approved by the user's social ties. These indirect pathways of influence now need to be considered in works examining the network flow of mass media messages.

Scholars seeking to identify opinion leaders on the Internet have often used network measures of influence and power. Research has found that in online spaces, structural metrics (like number of social ties) do not necessarily correspond to the ability to trigger large and far-reaching information cascades. As a result, in many cases the most effective way of disseminating information through social media would rely on ordinary users, and not on very popular celebrity accounts, to spread the word.

Somewhat surprisingly, the lack of association with information spread also holds for measures like TwitterRank that are based not only on social structure, but also on the topical similarity between users. This type of approach to evaluating the relative power of social media users is based on the understanding that influence is domain-specific rather than generic.

One purely structural metric that may be an exception from the rule is betweenness centrality, used to identify people in broker positions connecting different parts of a network. Some studies of social media have linked high betweenness to an increased capacity to influence the spread of information (Xu et al., 2014).

Analytical methods: advances and challenges

The structure of social systems is shaped by variety of factors. One major analytical challenge facing researchers who study network effects is disentangling the processes of *social influence* and *social selection*. Although they operate very differently, both mechanisms lead to the clustering of people who share similar opinions. This pattern, known as *network autocorrelation*, reflects the fact that social ties are more likely among people with similar characteristics.

Social influence, defined earlier in this text, works as a homogenizing force driving us to adopt the actions and opinions endorsed by our friends. *Social selection* (also known as *homophily* or *assortative mixing)* is the "birds of a feather" principle: people prefer to have ties with others who are in some way similar to them. As a result, personal networks are often homogenous with regard to multiple socio-demographic characteristics (McPherson, Smith-Lovin, & Cook, 2001).

In the context of the multistep flow of communication, it is particularly important to understand whether someone's opinion was influenced by their social ties, or if they selected social ties who shared that opinion to begin with. As *influence* and *selection* have identical results (the clustering of similar individuals), identifying the underlying processes can be challenging. Methodological problems stem from difficulties in ruling out confounding variables (Shalizi & Thomas, 2011). Contextual and selection effects can produce spurious correlations between network ties and individual outcomes, even when no interpersonal influence is taking place (Bramoulle, Djebbari, & Fortin, 2009).

These challenges can be demonstrated with a simple example. Imagine that Tom and Kate are friends, and we know both of them have the same political preference. We may suspect this is the result of social influence – perhaps one of them, an opinion leader, was able to convince the other to support a party or candidate. The patterns we observed, however, are also consistent with manifest homophily (Tom and Kate met at a rally and became friends because of their shared political ideology), or latent homophily (they bonded over a common interest in social issues which interest also shaped their similar political views). Social ties between individuals further suggest that they share a common environment: go to the same school, work together, live in the same neighborhood, or participate in the same online community. Environmental stimuli could affect both actors at the same time, resulting in what may from the outside look like a coordinated change in behavior. In the case of Tom and Kate, perhaps the local media they were both exposed to had a particularly convincing campaign supporting the candidate they both ended up choosing.

A number of analytical strategies are used to remedy confounding variable problems in models of social influence on individual behavior. Among them are natural or lab experiments (Centola, 2010), instrumental variables (Sovey & Green, 2011), matched sample estimation (Aral, Muchnik, & Sundararajan, 2009), and stochastic actor-oriented models (Snijders, Van de Bunt, & Steglich, 2010).

Experimental designs are a classic approach to establishing causality. There are two main ways of using them to test multistep influence hypotheses in a network context: by randomizing the network structure, or randomizing the node treatment. Naturally occurring social networks, however, are difficult to study that way, as is often impossible to rewire existing social structures or assign individuals to specific positions.

The instrumental variable approach is used in econometric models to address unmeasured confounding and simultaneous causation problems. This method relies on the existence of appropriate *instruments*: variables associated with the social influence measure, but not with its outcome (except indirectly). More generally, the instrument is correlated with the endogenous explanatory variable, but not with the error term in the explanatory equation. By regressing the influence or contagion effect on the instruments, we can get at the “clean” portion of its variance that we are interested in (Bramoulle et al., 2009).

Stochastic actor-oriented models (SAOM) are a relatively new, advanced technique designed to track the co-evolution of networks and behavior (Snijders et al., 2010). SAOMs are used to examine panel-based full-network data. They incorporate effects based on the structural position of actors, as well as their characteristics, examined at the dyadic level. One advantage of actor-based models is their ability to account for higher-level network structures that emerge as a result of various network formation mechanisms. When evaluating influence and selection, this approach can provide controls for a wide range of other effects related to network structure and individual behavior.

SEE ALSO:

Multistep Flow of Communication: Evolution of the Paradigm

Multistep Flow of Communication: Opinion Leadership and Personality Strength

Multistep Flow of Communication: Online Media and Social Navigation
Diffusion Theories: Logic and Role of Media
Diffusion Theories: News Diffusion
Diffusion Theories: Media as Innovation
Social Network Theory
Social Networking

References:

Aral, S., Muchnik, L., & Sundararajan, A. (2009). Distinguishing influence-based contagion from homophily-driven diffusion in dynamic networks. *Proceedings of the National Academy of Sciences, 106*(51), 21544-21549. doi: 10.1073pnas.0908800106

Bennett, W. L., & Manheim, J. B. (2006). The One-Step Flow of Communication. *The ANNALS of the American Academy of Political and Social Science, 608*(1), 213. doi: 10.1177/0002716206292266

Bramoulle, Y., Djebbari, H., & Fortin, B. (2009). Identification of peer effects through social networks. *Journal of econometrics, 150*(1), 41-55. doi: 10.1016/j.jeconom.2008.12.021

Brosius, H. B., & Weimann, G. (1996). Who Sets the Agenda: Agenda-Setting as a Two-Step Flow. *Communication Research, 23*(5), 561-580. doi: 10.1177/009365096023005002

Burt, R. S. (1992). *Structural holes: The social structure of competition*. Cambridge, MA: Harvard University Press.

Centola, D. (2010). The spread of behavior in an online social network experiment. *Science, 329*(5996), 1194-1197. doi: 10.1126/science.1185231

Friedkin, N. E. (1998). *A structural theory of social influence*. New York, NY: Cambridge University Press.

Friemel, T. N. (2015). Influence Versus Selection: A Network Perspective on Opinion Leadership. *International Journal of Communication, 9*, 1-20.

Katz, E. (1957). The two-step flow of communication: An up-to-date report on an hypothesis. *Public Opinion Quarterly*, 61-78. doi: 10.1086/266687

Katz, E., & Lazarsfeld, P. F. (1955). *Personal influence: The part played by people in the flow of mass communication*. Glencoe, IL: The Free Press.

McPherson, M., Smith-Lovin, L., & Cook, J. M. (2001). Birds of a feather: Homophily in social networks. *Annual Review of Sociology, 27*, 415-444. doi: 10.1146/annurev.soc.27.1.415

Menzel, H., & Katz, E. (1955). Social Relations and Innovation in the Medical Profession: The Epidemiology of a New Drug. *The Public Opinion Quarterly, 19*(4), 337-352. doi: 10.2307/2746773

Ognyanova, K., & Monge, P. (2013). A Multitheoretical, Multilevel, Multidimensional Network Model of the Media System: Production, Content, and Audiences. *Communication yearbook, 37*, 66-93.

Robinson, J. P. (1976). Interpersonal Influence in Election Campaigns: Two Step-flow Hypotheses. *Public Opinion Quarterly, 40*(3), 304-319. doi: 10.1086/268307

Roch, C. H. (2005). The Dual Roots of Opinion Leadership. *Journal of Politics, 67*(1), 110-131. doi: 10.1111/j.1468-2508.2005.00310.x

Rogers, E. (1995). *Diffusion of innovations* (4th ed.). New York, NY: Simon & Schuster Inc.

Shalizi, C. R., & Thomas, A. C. (2011). Homophily and Contagion are Generically Confounded in Observational Social Network Studies. *Sociological Methods & Research, 40*(2), 211-239. doi: 10.1177/0049124111404820

Snijders, T. A. B., Van de Bunt, G. G., & Steglich, C. E. G. (2010). Introduction to stochastic actor-based models for network dynamics. *Social Networks, 32*(1), 44-60. doi: dx.doi.org/10.1016/j.socnet.2009.02.004

Sovey, A. J., & Green, D. P. (2011). Instrumental variables estimation in political science: A readers' guide. *American Journal of Political Science, 55*(1), 188-200. doi: 10.1111/j.1540-5907.2010.00477.

Weimann, G. (1982). On the importance of marginality: One more step into the two-step flow of communication. *American Sociological Review*, 764-773.

Weng, L., & Menczer, F. (2015). Topicality and impact in social media: diverse messages, focused messengers. *PloS one, 10*(2), 1-17. doi: 10.1371/journal.pone.0118410

Xu, W. W., Sang, Y., Blasiola, S., & Park, H. W. (2014). Predicting opinion leaders in twitter activism networks: The case of the Wisconsin recall election. *American Behavioral Scientist, 58*(10), 1278-1293 doi: 10.1177/0002764214527091

Further readings:

Aral, S., & Walker, D. (2012). Identifying influential and susceptible members of social networks. Science, 337(6092), 337-341. doi: 10.1126/science.1215842

Valente, T. W., & Pumpuang, P. (2007). Identifying opinion leaders to promote behavior change. Health Education & Behavior, 34(6), 881-896. doi: 10.1177/1090198106297855

Author Mini-Biography:

Katherine Ognyanova is an Assistant Professor at the School for Communication and Information, Rutgers University. She does research in the areas of network science, media studies, social media, and political communication.