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WHITE PAPER

A Methodology of "How" to Communicate in the Age of Micro-Influencers

A network-graph-based approach to identify and track micro-influencers for effective communications

March 2023

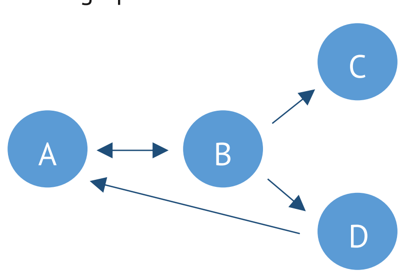
Why Micro-Influencers?

Shifting communication landscape, fragmented segments and mercurial consumers provide significant challenges for brands. Brand strategy dictates "what to say, to whom." Identifying "how to say" follows. The What-Whom part requires an unwavering long-term focus and commitment. Yet, the "How" part requires many tactics. Constantly searching for novel ways in grabbing the attention and pummelling the target audience with innovative attention-grabbers are essential for cutting through the ever-increasing clutter.

Tracking the elusive attention requires an intimate understanding of social. By figuring out the ways to track a brand's visibility among social media users, one can reach out to the target audience more effectively. To achieve that, it is important to extract connections between people who are engaged with the brand. It has been well documented that social media provides back-and-forth-type discussions that are effective in generating awareness and attractiveness. Who shares the information makes a difference. [1] argue that an influential or maven (who has many followers but seldom follows others) helps generate initial sparks, but during the cascading periods, the non-influentials play an important role in driving the conversations; and new users who gradually join the discussions help increase awareness.

Social Media as a Graph

One can think of social media as a network graph, where each user is represented as a circle or a node, and the connections between the users are as directed arrows, or edges. For example, if user A follows user B, who, follows A, C and D, and D follows A, the network can be represented in a graph as follows:



So, let's keep things simple and understand the basics with the above stylized network. We need to identify the best way to disseminate information using the above network. If one rephrases the objective as to "find the most effective way to communicate," Google's PageRank provides an alternative [2].

A Look at PageRank Algorithm

PageRank ranks the nodes based on their relevance in the network. When "relevance" is captured by a social network's following and follower data, a rank order of node importance can be identified. Let's dig deeper and see how this plays out in our simple network.

The algorithm is iterative. It starts with an initialization of nodes' ranks, all to the same values, to one. The initial value for each node than is 1. In iteration 1, each node disseminates the information based on following/ follower information, one step at a time. That is, all nodes only send the information using only one "hop." Since node C does not have any outside link, it acts as a sink. In order to break that, C is assumed to link with all other nodes in an equally random manner. So the info is disseminated to B, D and A with equal chance. This is captured by assuming that C has outgoing links to A, B and D. This results in the following rank orders as per iteration:

Iter'n	A	B	C	D	Sum	Distance (sq. diff.)
0	1.00	1.00	1.00	1.00	4.00	-
1	1.67	1.33	0.33	0.67	4.00	1.11E0
2	1.22	1.78	0.44	0.56	4.00	4.20E-01
3	1.30	1.37	0.59	0.74	4.00	2.28E-01
4	1.40	1.49	0.46	0.65	4.00	5.09E-02
5	1.30	1.55	0.50	0.65	4.00	1.28E-02
6	1.33	1.47	0.52	0.68	4.00	7.97E-03
7	1.34	1.50	0.49	0.66	4.00	2.30E-03
8	1.33	1.51	0.50	0.66	4.00	4.33E-04
9	1.33	1.49	0.50	0.67	4.00	2.58E-04
10	1.33	1.50	0.50	0.67	4.00	9.77E-05

The convergence is achieved relatively fast for this simple network as can be seen from the data under the distance column. The amount of information is always 4 as no information is lost through the iterations. The algorithm picks B, A, D and C, in the order of importance. Thus, it is best to use B as the most preferred node to start the dissemination. Furthermore, the ranks provide the relative importance of different nodes. If we assume that each node is an author in our social network. A brand should try to pick B first. If B does not want to act as the “spokesperson,” author “A” with an 89% success similar to B (1.33/1.5) may be the next alternative.

When the network is large, it is possible to represent the flows using a Markov process. The links between nodes can be represented by a MxM matrix. If one has a network with 800 million authors, an 800 million by 800 million (sparse) matrix can be created. By taking the power of the matrix, say to the power of 100, the resulting steady-state matrix represents the final ranks. A sum across the rows for each column will provide the page ranks for each of the 800 million authors.

Identifying Micro-Influencers with a Communication Objective

Network data is a good initial starting point. But, given the multiple dimensions of interests and different types of motivations of using social, it is hard to argue that a single algorithm may do wonders. A more specific use requires a careful consideration with more advanced features to create special-purpose network structures.

In order to be more concrete, consider an example. Take a random public profile in Twitter. Each user comes with a follower/ following information. It is easy to see the profile information as well as the following and follower data. Below, one can see that Dr. Northrup has 114.5 K followers and 623 followings based on the profie info:

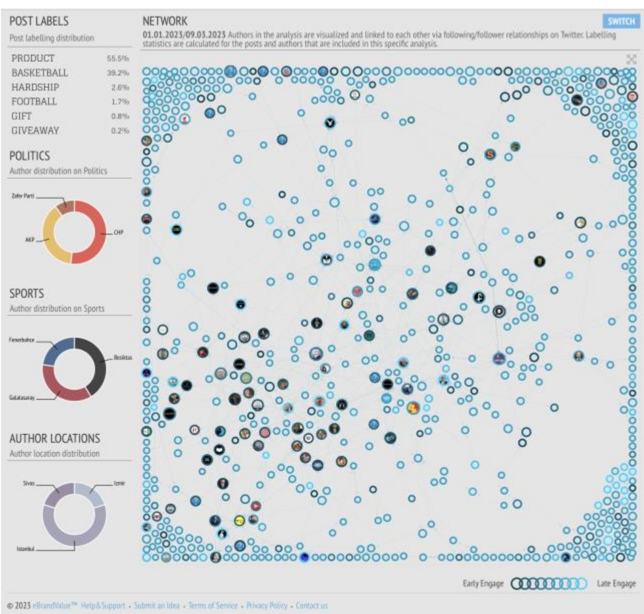
One can also identify each of the following and follower IDs by clicking on the links in the profile. Dr. Northrup, as apparent from the profile, is an expert when it comes to women’s health and wellness. However, when it comes to politics or entertainment, she may not be that important.

In general, different communication objectives require creation of different networks based on interests. One needs to extract new features such as authors’ lifestyles (activities, opinions, interests), geo-demographic information, etc. These are available from the contents shared, profile info and multimedia used in the profiles/posts. Using advanced NLP, Image processing and object/entity recognition techniques, many such features can be extracted. These features are included in powerful graph databases [3] which can be searched and filtered based on special interests in focus. eBrandValue’s Author Enrichment Feature (AEN) is developed for such purposes.

The AEN enables storing authors with many added features. Thus, rather than having only following and follower information, each author has many other attributes, including all the conversations they join in. The “Event” feature [4] can be used to filter and create a special network which can be visualized [6]. A blog entry, [5], provides additional information.

Not only ranking the users who are already engaged with a topic, but also to come up with new collaboration suggestions for a focal topic may also be an objective. By looking at the engaged network, and by identifying the most closely linked authors to the engaged authors, but not engaged with the conversation so far, eBrandValue can find out and report who would be highly influential in this network. By including such individuals, the topic dissemination can be much more powerful and engaging.

An example visualization of the network amongst the authors who already engaged with a topic are filtered based on specific keywords and search terms may look like this:

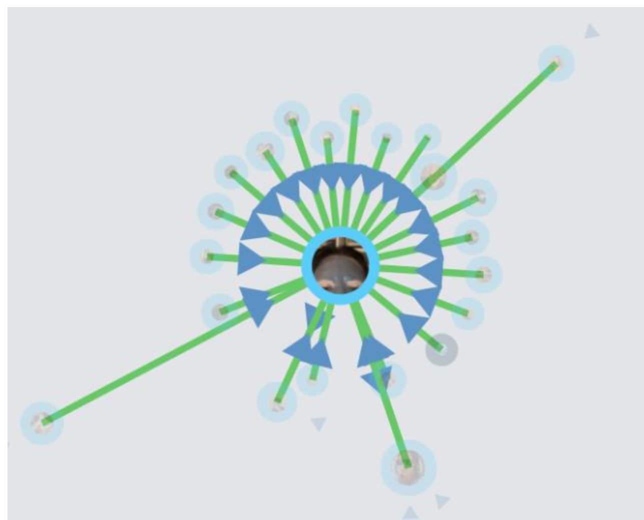


In the above visualization, each author is represented with a circle. The circle circumferences differ based on their pageRank scores. The circle colour captures an added dimension and provides the time of engagement. Early engagers are closer to dark blue and late engagers are closer to light blue.

On the left of the network graph, the authors' common labels are listed. These labels may include many different categories of interest. It is possible to screen the authors based on their interests by clicking on the label.

The analysis may contain hundreds of thousands of unique users. Edges are ranked between the users with respect to the PageRank score of the users that each edge connects. The algorithm only brings the most important ones with the highest scores to the screen. An edge between two high-scoring users would be visible on the network.

As one hovers the mouse over a node, one can see the followers with green highlighted edges with forward arrows. The reverse pointing arrows represent the reverse relationships.



When one clicks on a node, one can also scroll through the content that the node (author) created. The content should be relevant to the conversation of interest. Thus, one is able to observe the relevant content associated with the node and see the logic of including in this network.

Network users often form clusters among themselves and it is surely an insightful investigation to look for what common features communities present within themselves. For instance, one community can be a group consisting of users that are frequently engaged in sports and another community can be defined as a group of pop-culture accounts. You can define communities and detect users that are gateways between clusters. Those users would be key for reaching out to different segments of the audience.

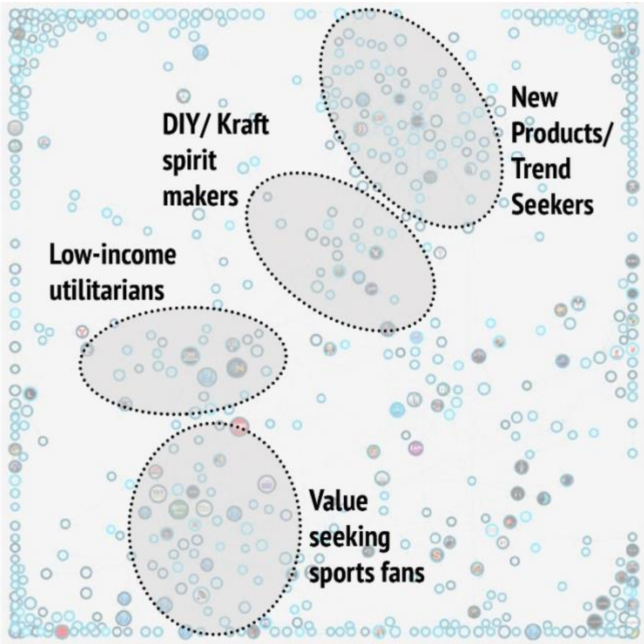
A Case Study: How to Influence Quality Perceptions in the Presence of Inflation and Competitive Pricing Pressures

During Q3'22, in the face of inflationary pressures and pricing related stresses on brands, our client, an international adult beverage company, asked us to identify how best to communicate the prestige status of their brands. The competitors introduced low-cost alternatives. Our client's brands thrive on reputation. Status and image attributes conveyed by the brands are important for the client. How to defend the brand attributes and how much margin is worth for the prestige status for consumers are not easy questions to answer. Further, the market reacts fast to the macro-economic and competitive developments. Long-term experiments and conjoint studies cannot provide fast, reliable actionable information. Our client sought to strengthen the prestige image by focusing on the social media communications as a fast and reliable strategy. eBrandValue's Brand Scores provide an accountable way to track the sales elasticity of such communications [7].

eBrandValue platform has been tracking close to 200 adult beverage brands and many generic category level keywords real time based on social. One special feature of eBrandValue platform is its ability to associate authors with the sector-specific brand affinities. Although an author may produce many contents associated with different brands, one brand may stand-out above all the others when it comes to frequency, valence and salience. For example, the below author is labelled as a Chivas Regal consumer although there are many brands the author engages with in this specific post. But, when the author's previous posts are taken into consideration, Chivas Regal dominates the rest, hence the preferred-brand label.

The brand-affinity label enriches the author data and enables identifying the authors whose brand affinities switch between the low cost alternatives and the premium brands. It is possible to filter the authors who had the client's brand affinity earlier, but now, who are somewhat inclined to or already engaged with low-cost, economy brands as part of their adult beverage consumptions. Using the Event feature, we created such a filter. We extract all the follower relationships among the filtered authors. This basically builds the network below with all the relevant contents. The contents the authors produce when changing their brand affinities between the prestige and economy brands and facing economic hardship can be easily seen and investigated by clicking on the specific node (author).

As discussed before, the network graph uses a force-directed algorithm and clusters the authors closer based on their following-follower information and the "hops" in between them when reaching one another in the network. Thus, the analysis reveals the existence of four segments.



For each cluster, looking at the PageRanks, it is possible to identify the authors who are potentially more likely to spread influence within the cluster. The client decided to exclude certain segments, namely, low-income utilitarians. With the remaining three segments, the identified micro-influencers are included as partners for the communication strategy. Further, the client created special promotions, events and activations based on the suggestions of micro-influencers.

Sources

1. Akcura, T., Altinkemer, K. & Chen, H. Noninfluentials and information dissemination in the microblogging community. *Inf Technol Manag* 19, 89–106 (2018). Available at https://link.springer.com/article/10.1007/s10799-017-0274-z.

2. https://en.wikipedia.org/wiki/PageRank

3. https://neo4j.com

4. https://www.ebrandvalue.com/en/product/#event-analytics

5. https://www.ebrandvalue.com/en/blog/network-analysis/

6. https://en.wikipedia.org/wiki/Force-directed_graph_drawing

7. https://www.ebrandvalue.com/en/blog/new-branding-paradigm/

About eBrandValue

eBrandValue launched in 2012 with the mission of synthesizing social data to help brands bridge the gap between social sentiment and the real-world marketing and sales strategies that govern them. The founders bring over forty years of marketing and sales insights gathered from positions at some of the world’s most prestigious institutions. The firm is backed by a robust team of PhDs, developers, and analysts that sift through many terrabytes of data to ensure the value of their clients’ brands keep rising.

Contact eBrandValue today to measure and increase the sales-correlated value of your brand.

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