Understanding the power of social influence marketing

By **Xi Chen**

Traditional marketing communication tools like digital advertising and promotions are still useful for making people aware of products, but do not effectively persuade them to make a purchase. This is because consumers are much more informed and take a longer period of time to make a purchase decision than before.

Ten years ago, if you wanted to buy a laptop, you would pop into a Dell store. Today you are more likely to read online reviews, or watch a product demonstration on YouTube, before eventually choosing which make or model to buy.

The challenge for consumers is knowing which source of information to trust. Each review will communicate different things, and sometimes offer conflicting opinions. This makes each purchase decision more complex and lengthier. Consumers thus turn to heuristics, such as personal recommendations from their networks. We are all social animals, after all. If my friend tells me they liked a laptop they bought, I'll likely trust his words more than that of an unknown technology product blogger, and certainly more so than an advert.

This is where the power of social influence marketing comes in. This is a relatively new form of digital marketing that leverages the social influence of individuals on social networks to influence consumer behaviour, often celebrities with massive followings on the likes of Instagram, who are known as influencers. So a marketer might send an influencer a free product to review and post about. The hope is this social

media star's trusted and valued opinion will motivate others to purchase the product.

Understanding influence

Companies often purchase massive data sets from social media firms with millions or billions of users, such as Twitter and Facebook, to work out which influencers to use for marketing campaigns. This data will shed light on things like how many followers they have, or how often they post about certain products online and the reach of those posts.

The problem is, marketers have little sense of how influential these people really are, despite their cult stardom online. This is because, when surveyed, consumers themselves find it hard to remember and quantify how much impact someone has had on their purchase decision. That's because it takes people a long time to make a purchase and much could have happened in that time that might have influenced their choice. It's almost impossible for them to accurately quantify the impact of social influence on their purchase decision.

It's also difficult to work out how much social media users influence each other based on the secondary data that

companies buy from the social media giants. Often, marketing managers assume that if people have a similar purchase history, they are likely to be able to influence each other. But correlation does not necessarily mean causation. People are often friends because they have similar interests already, rather than each friend driving the interests of the other. Environmental factors also come into play. People who live in the same area probably consume the same advertisements, leading them to purchase the same products.

Social influence

Fellow researchers Ralf van der Lans, Michael Trusov and I have developed a mathematical model that is much more effective at measuring social influence than traditional techniques; one that, potentially, has big implications for companies' marketing efforts.

The idea comes from game theory – a theoretical framework for conceiving social situations among competing players that was pioneered by famous mathematicians John von Neumann and John Nash. So, in other words, the outcome of the decision an individual makes is dependent on the decision that all the players of a game make.

Take, for example, a poker game, where people are playing without knowledge of their opponents' cards and make decisions based on what they think their opponents will do. If they could see all their opponents' cards, they could work out the best decision to make using maths. Each time they play the hand they would have played if they could see everyone's cards, the better they perform,

and vice-versa. This is known as an incomplete information game.

To build our mathematical model, we gathered data on the login decisions of more than 25,000 users of an online social game over 30 days. Tasks in the game require team efforts, making social influence an important consideration for users' login decisions. We examined whether the users logged in, or not.

We also assumed that people's perceptions of their friends' login decisions would affect their own login decisions, positively and negatively. For example, we assumed that, if people thought that a large proportion of their friends were online, they would react in one of two ways: be more motivated to log in and socialise, or the opposite.

We also assumed that if people were more motivated to log in, this effect would be multiplied across their friendship group, with the behaviour of one person influencing their friend, and then that friend's friend, and so on. In game theory, this is known as fictitious play.

But it's not always the case, we supposed. And indeed, social repulsion, a desire to be unsociable, is gaining ground, with Facebook allowing people to hide their behaviours from their friends, for instance.

To determine the influence of users playing our online game, we used a counterfactual scenario: what impact does removing one person from the game have on the total number of login decisions of all the remaining players? If the number of login decisions went down, that indicated the removed player had social influence: people wanted to play with them and followed the trend they set. Using this framework, we ranked users based on their influence, with the most influential players the best targets for influencer marketing.

We used a community detection algorithm to create control variables to partial out spurious correlation and cleanly quantify social influence. If not controlled, these spurious correlations, due to people facing similar environments, would be attributed to social influence. The community detection algorithm is also efficient and scalable to a network of millions of consumers.

We dubbed our model the optimal approach to social influencer marketing, and compared it to two other, commonly-used approaches: the responder approach, whereby people who ▶

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Practical implications

There are numerous practical implications for the research, including the finding that predicting consumer behaviour is far different from searching for the effects of influence.

Our research also shows that usage patterns are less effective for social influence marketing. Instead, marketers should leverage what is known as the social multiplier effect, or targeting a small group of members who are proven to be influential through how they respond to social influence over a long period of time.

Indeed, we found that the 1,000 most connected users have significantly lower average responsiveness than the least connected 1,000 users. The influencer approach, which considers both direct responsiveness and connectedness of users, significantly outperforms all other approaches.

The best targets for social influencer marketing, then, are those most likely to react to marketing and who have the largest online social networks, made up of people who are likely to respond to the target's own action. ∎

frequently purchase products are targeted; and the hub approach, in which people with large social media followings are assumed to have influence over them.

The results showed that our model vastly outperformed both the hub and responder method, by 22.25 per cent and 27.49 per cent, respectively. This is because people are often connected with those who are similar to themselves, so they likely already buy the same products. This is called assortative mixing. And not only will they not buy the products, they might tell other people not to as well. This might be because they are already attached to a brand's product, and might not want to purchase newer versions.

Our model's outperformance, then, can also be attributed, in part, to the fact that it considered the heterogeneity of consumers, who have both a positive and negative influence on their online networks.

We also found that the performance of targeting influential users not only depends on their network position, but

also on the time that consumers were hit with advertising. In the online game, there were times of engagement that were more preferable to some users but less popular among others. How users respond to their friends might also depend on the time of the day.

When targeting individuals, we assume a gaming company faces a decision of choosing one of four quarters of the day (12am-6am, 6am-12pm, 12pm-6pm, and 6pm-12am). In a uniform targeting approach, the company selects an optimal quarter to stimulate all of the targeted individuals. In the second scenario, called personalised timing, each targeted user is stimulated at a personalised optimal quarter, which depends on its responsiveness as well as the responsiveness of its peers.

Benchmarked with an approach that does not consider timing, the timed approach improves the targeting performance by 27.43 per cent. Moreover, using a personalised promotion schedule further improves the targeting performance by 15.13 per cent.

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