

INFLUENCER VIDEO ADVERTISING IN TIKTOK

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IN THIS BRIEF

Influencer videos on the TikTok online platform have emerged as a major, multibillion-dollar force in marketing. We explore what differentiates influencer videos that drive many sales from those that drive only a few.

We develop an algorithm that can be used to predict the sales lift of TikTok influencer videos. This algorithm uses a Convolutional Neural Network to quantify the extent to which the product is advertised in the most engaging parts of the video, creating what we call a motion score, or m-score for short.

Videos with higher m-scores lift more sales, especially for products that are bought on impulse, are hedonic, or inexpensive. A video that only engages, or that simply features the product throughout, will not necessarily have a high m-score. It needs the product to be featured at the right place and the right time.

Stakeholders in the TikTok ecosystem can use m-scores to aid video design, to select videos for various campaigns, and to align incentives for influencers and brands.

Tik Tok is among the major online platforms blurring the line between content and commerce. Some creators of TikTok videos, known as influencers, simultaneously entertain their audiences and sell them products.

Our research team studied the difference between TikTok influencer video ads that drive many sales and ones that drive fewer sales. We also studied whether it's possible to predict which TikTok influencer video ads will drive more or fewer sales.

To answer these and other related questions, we developed an algorithm that predicts TikTok influence video sales lift using a new metric that we call motion score, or m-score, for short. This statistic is based on an algorithm that quantifies the extent to which the product is advertised in the most engaging parts of the video.

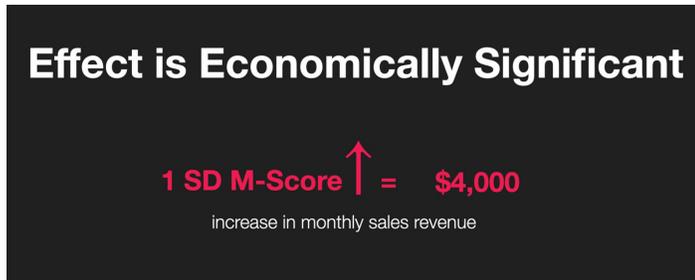
We conclude that a one standard deviation increase in a TikTok video's m-score translates into an additional \$4,000 in monthly sales, an average increase of approximately 12% (Figure 1). We also find that influencer videos are most effective for impulsive, hedonic, and inexpensive purchases. Finally, we find that a video's sales lift can be curtailed by incentive mismanagement, which occurs when an influencer promotes themselves rather than their products.

THE RISE OF INFLUENCER VIDEO ADS

The impact of TikTok, an online platform for short videos, is huge and fast-growing. In 2020 this online platform was the

world's most frequently downloaded app, and now TikTok has more than 1.4 billion monthly users worldwide. The platform's advertising revenue is estimated at more than \$16 billion a year.

Fig. 1: A video's m-score correlates with additional sales



The TikTok platform also has approximately 3 million influencers — video ad creators who simultaneously entertain viewers while selling them products. These influencers have quickly emerged as major marketers. One of TikTok's biggest influencers in China, a young man named Li Jiaqi, recently sold more than 7 million units of lipstick in just one day, worth an estimated \$145 million. Such huge marketing impact has caught the attention of companies including Walmart, the world's largest retailer, which recently tested product-driven TikTok videos.

It still remained unclear, however, why some TikTok influencer video ads like Li Jiaqi's drive many sales while others drive few. We set out to develop a way to predict the effect of influencer videos on product sales by drawing on the theory of bottom-up attention from cognitive psychology and neuroscience (for example, Milosavljevic and Cerf, 2008).

Bottom-up attention is a rapid, automatic form of selective attention that depends on the intrinsic properties of the input. It's also known as saliency-based attention, indicating that the more salient, or outstanding, an object, the higher the probability of it being noticed. By contrast, top-down attention is volitional, focal, and task-dependent; it can be likened to a spotlight that enhances the processing of a selected item (Koch 2004).

RELATED MARKET RESEARCH

Our work is inspired by several streams of marketing research.

First, we address a problem in influencer marketing (Avery and Israeli, 2020). Influencer marketing — a large industry currently estimated at \$10 billion and growing by 50% a year — involves the influence of key individuals or opinion leaders to drive brand awareness among consumers and to sway their purchasing decisions (Brown and Hayes, 2008). The main channel through which influencers wield their impact is social media.

Previous work on influencer marketing has studied the effect of influencer attributes on self-reported purchase intent. For example, Lou and Yuan (2019) found that an influencer's trustworthiness, attractiveness, and similarity to their followers affect brand awareness and purchase intent. In related work, Schouten et al. (2020) showed that influencer endorsements are more effective than those from celebrities, and that the effect is mediated by a higher perceived similarity and trust.

Overall, our area of focus, influencer video advertising, has been understudied. One exception is Rajaram and Manchanda (2020), who analyzed the relationship between YouTube influencer video ad content and video views, interaction rates, and sentiment. In contrast, we focus on sales conversion and sales lift from influencer video ads.

COMPUTING M-SCORE

The algorithm we developed takes unstructured data from actual TikTok videos and transforms it into structured information in the form of compact, intuitive, and interpretable summary statistics. Not only is this information predictive of sales lift, but it can also be applied before a video is published. We call this summary statistic motion score, or m-score.

The motion concept comes from an analogy with Newton's first law of motion: an object will remain at rest or continue to move at a constant velocity unless acted upon by an external force. Similarly, a video ad will not produce sales lift until it has both content engagement and product placement. More specifically, variations in engagement over the pixel space and time of a video create force fields with varying strength.

Drawing further on our analogy, we find that the overall motion (sales lift) is strong if the object (product placement) appears

where the force (content engagement) is also strong.

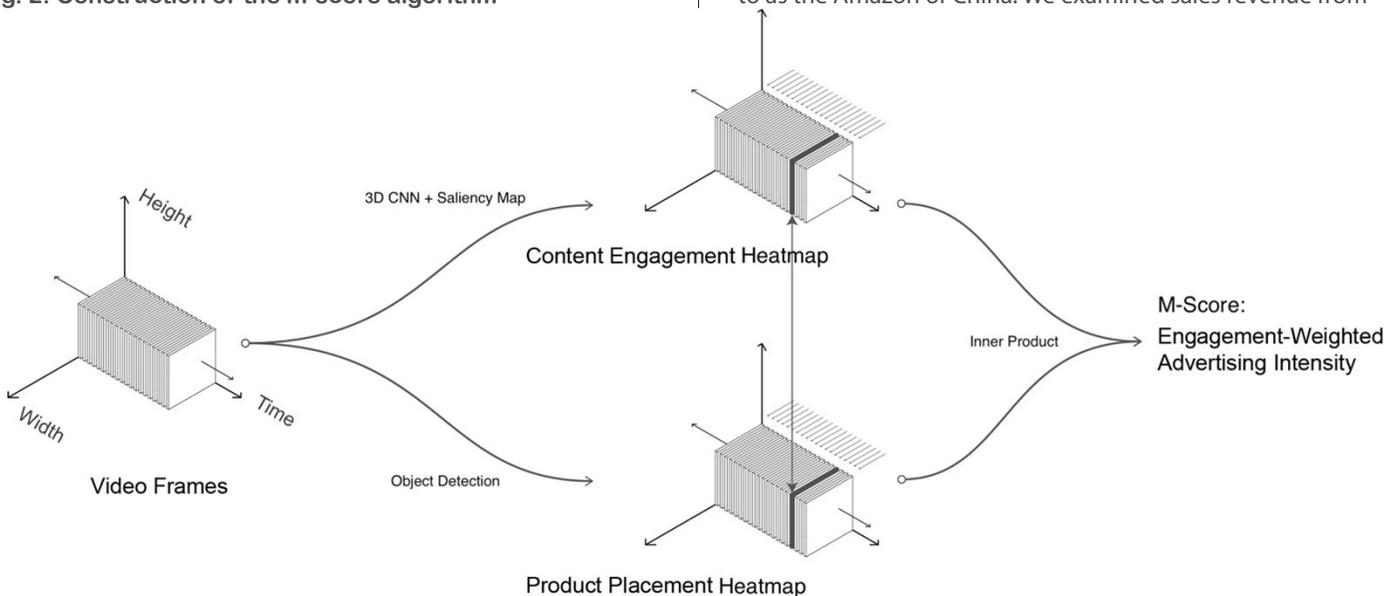
Based on theories of bottom-up attention, our hypothesis behind m-score is, other things being equal, that the more salient and engaging an advertised product is in an influencer video ad, the more effective the video ad will be in lifting sales. To put this into operation, we define a video's m-score as its average pixel-level engagement-weighted advertising intensity. We compute this in three steps:

Step 1: We constructed a 3D matrix that we call the content-engagement heat map. The matrix's three dimensions are the height of each video frame in pixels, the frame's width (also in pixels), and the video's overall length in seconds.

This content engagement heat map is a pixel-level saliency map that shows the gradient of video-level engagement (such as number of likes and shares) for each and every pixel. The engagement scores are estimates created by a 3D Convolutional Neural Network trained to work from the video-level engagement data from some 30,000 video ads.

Step 2: We constructed a 3D product placement heat map (Figure 2), which shows whether the product being advertised is present at a given pixel in a given video frame.

Fig. 2: Construction of the m-score algorithm



an image of the product to each frame of the video. To do this, we use an object-detection algorithm called the scale-invariant feature transform. We estimate the product placement heat map by matching invariant feature transform.

Step 3: We computed m-score using the two 3D matrices, normalized by the total number of pixels of the video. This normalized inner product can be interpreted as the average pixel-level, engagement-weighted advertising intensity (Figure 2). In other words, it's the extent to which the product is shown in the most engaging parts of the video ad.

We further hypothesize that a video ad with a higher m-score will be more effective in lifting sales than one with an m-score that's lower. It is important to note that an m-score measures the complementarity between content engagement and product placement. A video that only engages, or that only features the product throughout, will not necessarily have a high m-score. To earn a high score, a video must feature the product at the most engaging pixels and time (Figure 2, below).

TESTING THE HYPOTHESIS

We tested our approach by analyzing a proprietary dataset. This set contained some 40,000 influencer video ads from the original Chinese version of TikTok, as well as their corresponding product sales revenue on Taobao, a website sometimes referred to as the Amazon of China. We examined sales revenue from

March through June of 2019. We focused on the Chinese version of TikTok because of its mature ecosystem around influencer video advertising. TikTok in China offers an online marketplace, known as Xingtou, which has attracted more than 330,000 influencers and 760,000 product sellers.

Consistent with our hypothesis, we found that m-score positively predicts the sales lift of a video ad. Specifically, as noted in Figure 1, a one standard deviation increase in m-score is associated with a 12% increase in sales revenue of the advertised product.

Notably, neither engagement nor advertising intensity — the latter being the total number of video pixels in which the product appears — alone had an effect on sales lift. Rather, it is the complementarity between the two components that drives sales, highlighting the unique predictive power of m-score.

To understand the applicability of our algorithm to different product categories, we conducted a supplementary survey to classify advertised products in our data. We found that our algorithm is more effective in product categories associated with impulse purchases, hedonic consumption, or lower prices. These kinds of products are also popular choices for the growing new field of entertainment commerce.

CONCLUSIONS

Our algorithm can be put into practice in several ways. First, influencers can use it as an automated tool to test and modify their videos for better sales lift. Second, the content engagement heat map can serve as a useful tool to understand video engagement. Third, m-score introduces a new contractual instrument to the entertainment commerce space. Product sellers can use m-score to screen candidate videos or directly write a contract.

One key practical advantage of m-score is that it can be computed before a video ad is released, without relying on in-consumption user data such as eye tracking or live comments. This means the algorithm is highly scalable; it can be used to evaluate a large number of candidate videos very quickly.

More specifically, influencers can use m-score to aid video

content development in real time, and product sellers can use m-score as a novel contractual instrument. For example, product sellers can compensate influencers based on the m-score of their video ads. In comparison, the current industry practice of engagement-based compensation has been shown to be ineffective, whereas sales-based compensation makes influencers accountable for product sales but exposes them to various factors beyond their control (such as perceived product quality, which is difficult to put into a contract). In this sense, m-score can serve as a metric to help clarify the attribution of sales outcome between product sellers and influencers.

Finally, entertainment commerce platforms can leverage m-score to launch various features to improve transaction efficiency. For example, a platform could highlight its m-score as a key performance index of influencers. Providing an m-score alongside engagement metrics can also help product sellers choose influencers with richer information.

REPORT

THE FULL RESEARCH PAPER CAN BE FOUND [HERE](#)

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REFERENCES

Avery, J., Israeli, A. (2020). Influencer marketing. Harvard Business School Case, N9-520-075.

Brown, D., Hayes, N. (2008). Influencer Marketing. Routledge.

Koch, C. (2004). The quest for consciousness. *Engineering and Science*, 67(2), 28-34.

Lou, C., Yuan, S. (2019). Influencer marketing: how message value and credibility affect consumer trust of branded content on social media. *Journal of Interactive Advertising*, 19(1), 58-73.

Milosavljevic, M., Cerf, M. (2008). First attention then intention: insights from computational neuroscience of vision. *International Journal of Advertising*, 27(3), 381-398.

Rajaram, P., Manchanda, P. (2020). Video influencers: unboxing the mystique. SSRN 3752107.

Schouten, A. P., Janssen, L., Verspaget, M. (2020). Celebrity vs. influencer endorsements in advertising: the role of identification, credibility, and product-endorser fit. *International Journal of Advertising*, 39(2), 258-281.

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