Social Media Roadmap: Using Deep Learning to Predict the Popularity of Instagram Posts by Plastic Surgeons

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Abstract

Background

The proliferation of social media in plastic surgery poses significant difficulties for the public in determining legitimacy of information. This work proposes a system based on social network analysis (SNA) to assess the legitimacy of information contributors within a plastic surgery community.

Objectives

The aim of this study was to quantify the centrality of individual or group accounts on plastic surgery social media by means of a model based on academic plastic surgery and a single social media outlet.

Methods

To develop the model, a high-fidelity, active, and legitimate source account in academic plastic surgery (@psrc1955, Plastic Surgery Research Council) appearing only on Instagram (Facebook, Menlo Park, CA) was chosen. All follower-followed relationships were then recorded, and Gephi (https://gephi.org/) was used to compute 5 different centrality metrics for each contributor within the network.

Results

In total, 64,737 unique users and 116,439 unique follower-followed relationships were identified within the academic plastic surgery community. Among the metrics assessed, the in-degree centrality metric is the gold standard for SNA, hence this metric was designated as the centrality factor. Stratification of 1000 accounts by centrality factor demonstrated that all of the top 40 accounts were affiliated with a plastic surgery residency program, a board-certified academic plastic surgeon, a professional society, or a peer-reviewed journal. None of the accounts in the top decile belonged to a non–plastic surgeon or non-physician; however, this increased significantly beyond the 50th percentile.

Conclusions

A data-driven approach was able to identify and successfully vet a core group of interconnected accounts within a single plastic surgery subcommunity for the purposes of determining legitimate sources of information.

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Background

Previous studies have used artificial intelligence and a combination of image features, text analysis, and social context to predict the popularity of images online/ on social media.

Objectives

The aim of this study was to predict the popularity of images posted by plastic surgeons and quantify the social context and content- specific factors that contribute to their popularity. More generally, we sought to answer the question: "What makes a plastic surgery- related image popular?"

Methods

A list of US- listed plastic surgeons was generated by scraping the ASAPS webpage. Instagram accounts associated to individual surgeons were identified manually. For prediction purposes, we deployed a random forest machine learning algorithm on the dataset of all Instagram posts to train it to predict the log- scaled popularity of Instagram posts, quantified using Spearman's rank correlation (ρ).

Results

Across 2,183 US- based ASAPS members, we identified accounts associated to 58.2% (n= 1,272) of plastic surgeons. The mean number of followers was 5,894 (range 0- 521,896). Across all accounts, we identified 395,537 posts. The combination of all content- specific and social context indicators generated a rank correlation of 0.74 (strong predictive ability). Our deep learning content analysis revealed that "swimming trunks", "lab coat", and "gas mask" (surgical mask) had a strong positive impact on popularity.

Conclusion

While previous studies evaluated virality of text and images unrelated to plastic surgery on the internet, this study achieved a significant rank correlation between the predicted and actual popularity of Instagram posts by ASAPS- member plastic surgeons.

Introduction

Instagram has overtaken Facebook as the social media platform of choice for 18- to 34-year-olds, with nearly half of its one billion active monthly users logging on daily and thousands of posts being uploaded every minute[1-4]. With the rise of social media use, there has been a commensurate increase in resources being devoted to understanding how information propagates across these platforms. Previous studies have described virality and influence in social media marketing, by modelling the spread of content and seeking to maximize the number of users reached[5-7]. These have found that spread is heavily reliant on users voluntarily sharing content they see, and that the actions of a few well- positioned individuals within a network can profoundly impact the choices made by their peers. More recently, studies have used artificial intelligence (AI) and a combination of image features, text analysis, and social context to predict the popularity of images online/ on social media[8-13]. In commercial settings, accurately predicting popularity can help value sponsored content.

As 49% of all plastic surgery patients and the majority of patients undergoing cosmetic procedures are between 40 and 54 years old (according to the American Society of Plastic Surgeons [ASPS]), the rise of social media represents an opportunity for plastic surgeons to diversify their offering and educate/ communicate directly with a new patient demographic[14]. While current guidelines exist to establish social media best practices and ensure the ethical use of these tools, there is no evidence- based consensus on how plastic surgeons can maximize the reach of their social media presence[15-18].

The aim of this study was to predict the popularity of images posted by plastic surgeons and quantify the social context and content- specific factors that contribute to their popularity. More generally, we sought to answer the question: "What makes a plastic surgery- related image popular?" We identified Instagram accounts associated to members of the American Society for Aesthetic Plastic Surgery (ASAPS) and analyzed account details and features of all individual posts using deep learning (DL) technology to provide the first data- driven summary of the current state of social media use by plastic surgeons. Our findings should equip members of the community with the tools necessary to leverage the full potential of the most popular social media platforms. For a primer on AI technology, and its applications in plastic surgery, please see Chandawarkar et al.[19].

Methods

Dataset

A list of US- listed plastic surgeons, current as of December 1st, 2019, was generated by manually scraping the ASAPS webpage (https://www.surgery.org/consumers/find-a-plastic-surgeon). Instagram accounts associated to individual surgeons were identified 1) from official surgeon/ practice websites, 2) by directly querying Instagram using full/ last names and all permutations of the terms "plastic surgery" and "cosmetic surgery" and 3) by directly querying Instagram using official practice names with and without all permutations of terms "plastic surgery" and "cosmetic surgery". Account associations with plastic surgeons were confirmed by manual review of content, accounts following, and accounts followed by.

For each account, we identified: username, Instagram verified status, Instagram private account status, number of followers, number of accounts followed by, number of posts, date of first post (as a proxy for account age), mean likes on ten most recent posts, and mean likes across all posts. The quotient of mean number of likes on ten most recent posts and number of followers was used to calculate engagement. Account engagement rates were categorized as: very low (< 1%), low (1- 6%), average (6- 12%), high (12- 20%), and very high (> 20%).

For each post, we identified: owner username, caption, number of likes, number of comments, location name, timestamp, hashtags used, and accounts mentioned. Content of each post was evaluated 1) using Facebook's content classification algorithm and 2) using the popular convolutional neural network (CNN) ImageNet Network[20,21]. The ImageNet project is a visual database of > 14 million hand- annotated images containing at least one image from > 20 thousand categories (e.g. banana, chair, swimming trunks, etc.). As part of the annual DL ImageNet challenge, known as ImageNet Large Scale Visual Recognition Challenge (ILSVRC), participants submit software programs that compete to classify a random sample of ImageNet images. In this study, all posts from all accounts were classified into one category using feature weights from ResNet-18, a recent top- performing ILSVRC classifier[22]. For each post's caption, we identified length in characters/ words and recorded most common terms used across all captions. Lastly, we used the SciKit Learn K Means Clustering (https://scikit-learn.org/stable/modules/generated/sklearn.cluster.KMeans.html) Python module to record the dominant color (encoded as a value for the hue, saturation, and value [HSV]) in each image.

Statistical and Deep Learning Analysis

Number of likes on each post was used as a proxy for popularity on Instagram. The heavily right- skewed popularity distribution across all posts was log- scaled to avoid having to exclude data on a set of the most popular outliers. For prediction purposes, we deployed a random forest machine learning algorithm on the dataset to train it to predict the log- scaled popularity of Instagram posts. We used Spearman's rank correlation (ρ) to quantify relationships between popularity and 1) social context input features (number of followers, followers- to- following ratio, number of posts, mean number of likes/ comments, Instagram verified status, Instagram engagement rate, and timestamp analysis) and 2) content- specific input features (object classification, dominant color analysis, and caption length)[8]. The data was randomly split five times such that a low negligible standard deviation could be achieved between test set predictions. In each split, 75% of instances constituted the training set and the remaining 25% made up the testing data. The machine learning analysis was conducted using the Python programming language deployed on the Project Jupyter platform. Captions were analyzed using the Matplotlib (https://matplotlib.org/), Collections (https://docs.python.org/2/library/collections.html), and Pandas (https://pandas.pydata.org/) Python modules to identify the most frequently used phrases, terms, and hashtags. Descriptive statistical analysis was performed with STATA (College Station, TX). Data was compiled with Microsoft Excel (Microsoft Corporation, Redmond, WA). All Instagram post data was collected on June 10th, 2020. All data collected for this study was published to Instagram between July 2011 and June 2020.

Results

Account Demographics

Across 2,183 US- based ASAPS members, we identified accounts associated to 58.2% (n= 1,272) of plastic surgeons, 13.6% (n= 174) of which were associated to practices with more than one surgeon. We identified 35 (2%) private accounts and 16 (1.3%) verified accounts.

Across all accounts, we identified 395,537 posts. The mean number of likes was 133 (range 0- 45,588). The raw and log- scaled distributions of number of likes are presented in Figure 1. The mean caption length was 46 words (range 0- 441) and 354 characters (range 0- 2,283 characters). The most common hashtags used were #plasticsurgery (28.1%, n= 111,023), #plasticsurgeon (13.9%, n= 54,787), and #cosmeticsurgery (9.3%, n= 36,840) (Table 1). The most common discrete words used were “patient(s)” (23.2%, n= 91,775), “skin” (18.1%, n= 71,646), and “call” (15.9%, n= 62,952) (Table 1). A sample of posts is presented in Figure 2.

Deep Learning Analysis

When we used indicators as input features to predict Instagram likes, mean number of likes (ρ= 0.64) and DL- assisted object classification (ρ= 0.19) achieved the highest Spearman rank correlations of all social context and content- specific indicators respectively. When combined, all social context indicators achieved a rank correlation of 0.22, while the combination of all content- specific indicators achieved a rank correlation of 0.67. The combination of all content- specific and social context indicators generated a rank correlation of 0.74 (Table 2).

Our DL content analysis revealed that “swimming trunks”, “lab coat”, and “gas mask” had a strong positive impact on popularity. “Convertible car”, “desk”, and “screen” had a moderately positive impact on popularity. “Lamp shade”, “lawn mower”, and “bookcase” had a negative impact on popularity. Analysis with Facebook’s (Instagram is a Facebook affiliate) native classification algorithm found that presence of one or two persons had a strong positive impact on popularity, while text in posts had a moderately negative impact on popularity.

Timestamp analysis revealed that posting on Wednesday, Friday, or Saturday and posting after 5:00 pm Eastern Standard Time (EST) had a strong positive impact on post popularity. Posting on Tuesday and posting between midnight and 2:00am EST had a strong negative impact on popularity. With respect to colors, on average, brighter and more vibrant colors had a greater influence on image popularity as compared to neutral colors, with shades of pink and red exerting the most influence on image popularity. A sample of dominant colors, ranked by influence on popularity, is presented in Figure 3. Lastly, a summary of the popularity matrix is presented in Figure 4.

Discussion

Previous studies have summarized use of social media, specifically Instagram, by plastic surgeons[23-28]. Others have described ethical best practices for sound adoption[29,30]. Unrelated to plastic surgery, data science practitioners and marketing experts have studied/ modelled virality, popularity, and the dissemination of information on the internet[8-11,31-34]. To the best of our knowledge, there are no studies at the intersection of plastic surgery, AI, and social media. This study quantified the ability of social cues and content- specific attributes to predict popularity of social media posts made by plastic surgeons.

It is first important to note the quality of the dataset of ASAPS members and affiliated Instagram accounts that underpins this study. While not its main purpose, this is the first study to 1) exhaustively quantify adoption of Instagram by members of a professional society of plastic surgeons and 2) plot adoption over time and elucidate the period of exponential adoption between January 2013 and December 2016 (r^2= 0.98 over that range). This is consistent with worldwide adoption of social media, and with a previous finding published by Chartier et al. that a few cautious early adopters in the field of plastic surgery pave the way for rapid adoption by the critical mass[3]. With nearly 60% of ASAPS- affiliated plastic surgeons having an Instagram account, our data supports the claim that members of the plastic surgery community have made it a priority to establish themselves on social media. It is also worth noting we identified seventeen plastic surgeons with "influencer" accounts (> 100,000 followers) and 102 with micro-influencer accounts (between 10,000 and 100,000 followers). On average, these account holders were early adopters of Instagram and contributed significantly to the trends described herein. However, further study of "influencer" plastic surgeons is necessary to gain a more granular understanding of their outsized popularity.

Very few (1.3%) accounts were Instagram verified. As per Instagram's support webpage, a verified "badge" appearing on an account page confirms the authenticity of a page representing a public figure, global brand, or celebrity[4]. The infrequency of account verification among ASAPS member plastic surgeons suggests that "the blue checkmark" should net yet be relied upon as a proxy for surgeon quality or board certification.

Our caption content analysis revealed a focus on aesthetic surgery practice promotion by the ASAPS membership (#tummytuck, #mommymakeover, #breastaugmentation, etc.). The popularity of words borrowed from the marketing vernacular such as "call", "reschedule", "results", and "happy" suggests that Instagram as it is currently used may be more useful to this cohort of surgeons as a marketing tool than as a patient education platform. This is consistent with the analysis conducted by Dorfman et al., who queried/ recorded the instances of twenty-one popular hashtags and found that plastic surgeons actually represent a minority of account holders posting with the top plastic surgery- related hashtags[23]. This study's findings in this cohort are in stark contrast with a previous study by Chartier et al. that described Instagram use by accredited integrated plastic surgery residency programs in the United States[3]. In that setting, popular terms and hashtags related primarily to medical education (#education, #residency, "congratulations", "research", and "medical student").

Across all posts, our social cue analysis achieved a combined Spearman rank correlation of 0.67. This is consistent with previous work published by Khosla et al., who analyzed 2.3 million images from the once popular image hosting platform Flickr and achieved a log-normalized rank correlation range of 0.66- 0.77 using the following platform- specific post attributes: mean number of views, user post count, number of Flickr contacts, duration of membership, Flickr Pro subscription status, tags used, post title length, and post description length[8]. Unsurprisingly, a user's mean number of likes was most predictive of number of likes on future Instagram posts – posts from a user with many likes on average are expected to gain more traction than posts from a user with few likes on average. The same directional logic applies to users with more followers, a higher follower- to- following ratio, and more posts. Interestingly, a user's mean number of comments correlated very strongly with their posts' popularity. With only sixteen verified accounts, Instagram verified status had the weakest correlation of all social cues (0.06) with post popularity. While interesting and novel, insights gleaned from social context indicators are of limited use to the plastic surgeon looking to make inroads with a new social media account.

Our content- specific indicator analysis revealed a Spearman rank correlation of 0.22 with image popularity. While this may appear much less significant than correlations based on social context indicators, predictions in this experiment were made using only AI- equipped classification, dominant color analysis, and caption length analysis and are of much greater value to the plastic surgery community. Our findings are again consistent with Khosla et al., who achieved a rank correlation range of 0.31- 0.40 using the following content- specific indicators: texture, color histogram, and DL object classification[8]. The difference in content- specific rank correlations can largely be attributed to asymmetries between datasets: Khosla et al. made predictions on a set of random images drawn from Flickr (containing objects and people) using an ImageNet classifier trained to recognize 1,000 object classes, while the dataset used in this study largely contained medical images that were often unrecognizable to the object classifier used in the DL portion of the study[8]. Nonetheless, clinical posts including before- and- after sets and "actions shots" of plastic surgeons outperformed other posts as evidenced by the strong positive impact on popularity of "gas mask" (clinicians wearing masks), "lab coat" and "swimming trunks" (including clinical images with "emoji" overlays, to hide genitalia and female nipples prohibited on Instagram, which were interestingly classified as swimming attire). While previous studies have found that images of people and faces gain more traction on social media than other content posted by comparable accounts, we found it particularly relevant that a large number of before- and- after sets (including images classified by Instagram's native classifier as "containing 2 people") also achieved outsized popularity[35,36]. Findings from our dominant color and timestamp analyses were unremarkable and largely consistent with findings from previous studies[8,9,37,38].

The results from and analyzes conducted as part of this study should be considered in light of multiple limitations. The main factor limiting our data collection was the inability to download content from private accounts, though this represented a small number of accounts surveyed. Regarding our AI analysis, our top- performing social context indicator (average number of likes) failed to account for time course since account creation. For example, our algorithm would incorrectly predict the popularity of an early post by an account that has since gone viral – mean number of likes at the time the image being predicted on was posted would be more predictive of popularity, but this would require computing several hundred thousand more data points.

Conclusion

While previous studies evaluated virality of text and images unrelated to plastic surgery on the internet, this study achieved a significant rank correlation between the predicted and actual popularity of Instagram posts by ASAPS- member plastic surgeons. Further studies conducted with larger datasets of images and more social context and content- specific indicators are needed to more accurately describe and make predictions on this type of content. We hope that the results of this study will serve as a roadmap to all plastic surgeons considering making Instagram a part of their practice.

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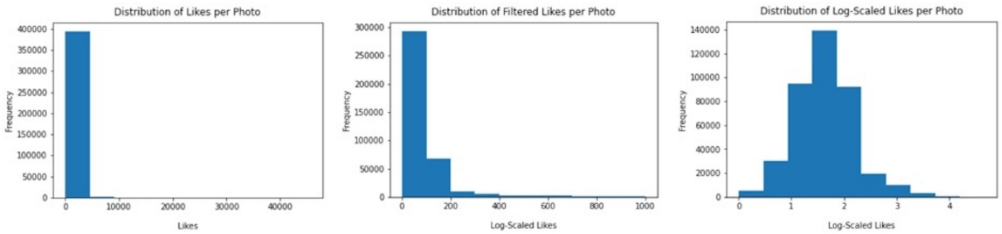

Figure 1. Distribution of likes per photo, filtered likes per photo (up to 1,000 total likes) and log- scaled likes per photo across all accounts.

165x38mm (300 x 300 DPI)

Figure 2. Random sample of posts ranked by increasing popularity from left to right.

106x57mm (300 x 300 DPI)

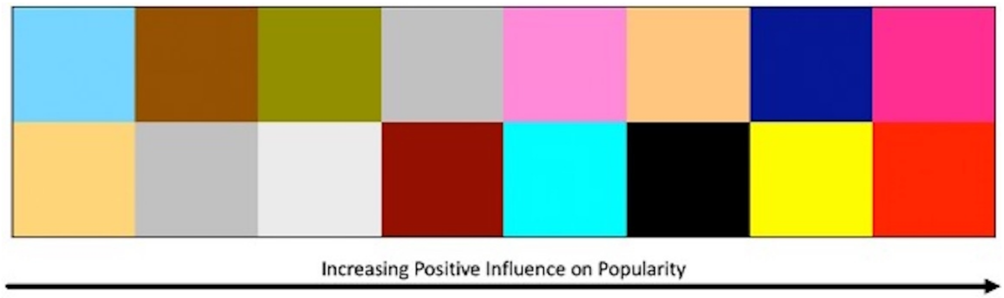

Figure 3. Random sample of colors ranked by increasing influence on Instagram post popularity.

98x29mm (300 x 300 DPI)

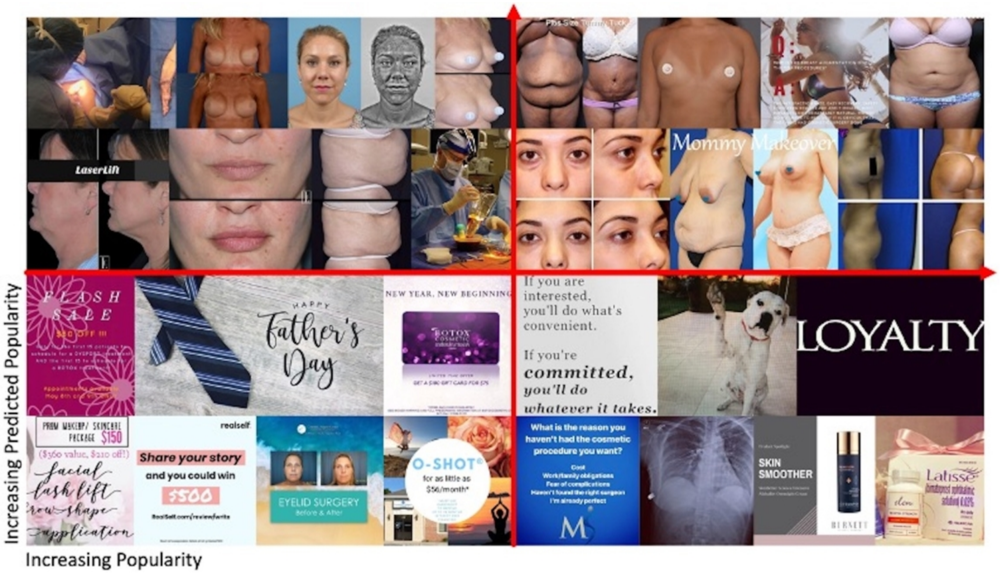

Figure 4. Random sample of posts ranked by increasing actual popularity from left to right and by increasing predicted popularity from bottom to top.

139x79mm (300 x 300 DPI)

Most Common Hashtags	Percentage of Posts	Most Common Discrete Words	Percentage of Posts
#plasticsurgery	28%	patient(s)	23%
#plasticsurgeon	14%	skin	18%
#cosmeticsurgery	9%	call	16%
#breastaugmentation	8%	surgery	15%
#botox	8%	breast	15%
#skincare	7%	today	11%
#tummytuck	6%	time	9%
#beforeandafter	6%	results	9%
#boardcertifiedplasticsurgeon	5%	happy	9%
#mommymakeover	5%	reschedule	9%

Table 1. Summary of the 10 most popular hashtags and discrete words used in captions across all posts.

103x31mm (300 x 300 DPI)

Social Context Indicator	Predictive Strength (ρ)
Number of followers	0.60
Number of followers:following ratio	0.40
Number of posts	0.30
Mean number of likes**	0.64
Mean number of comments**	0.54
Instagram verified status	0.06
Instagram engagement	0.44
Timestamp (day of week, time of day)	0.17
Combined (all social indicators)	**0.67**
Combined (social + content indicators)	**0.74**

*Of the given user

**On previous posts by the given user

Content- Specific Indicator	Predictive Strength (ρ)
Deep learning object classification	0.19
Native Facebook object classification	0.18
Dominant color analysis	0.14
Caption length (character count)	0.17
Caption length (word count)	0.14
Combined (all content indicators)	**0.22**
Combined (social + content indicators)	**0.74**

Table 2. Summary of the Spearman rank correlations associated to social context and content- specific indicators of Instagram likes.

165x52mm (300 x 300 DPI)