Theory and Evidence…..

The Influence of User-Generated Content

On Brand Perception

by

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An honors thesis submitted in partial fulfillment

of the requirements for the degree of

Bachelor of Science

Undergraduate College

Leonard N. Stern School of Business

New York University

May 2013

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I. Abstract and Acknowledgements

Abstract

This thesis aims to study the relationship between user-generated content and its influence on brand perception. In particular, this thesis studies the network and platform particularities of Instagram as a means to understand the influence of content on perception, as its photograph emphasis and usage of portraying filters provide an interesting context for these relationships. The study incorporates variables such as likes, followers, number of photographs, and filter usage to analyze these relationships. This study utilized 3 datasets of 5,000 photos for Starbucks, Dunkin' Donuts, and Jamba Juice to create a basis for comparison across a similar category, the fast beverage category. The analysis confirms that some of the prior brand associations permeate the network and also determines which brands in the fast beverage category have more or less influence than the users who hashtag their brands. Some peculiarities in the data also provide insight as to what data analysts can expect to find in these large datasets. Results of this study can provide a basis for various recommendations to how brands can better leverage the learnings from User-Generated Content to be more effective on this relatively new platform.

Acknowledgements

I would like to acknowledge Professor Arun Sundararajan, my thesis advisor, for his expertise and knowledge as well as his recommendations regarding tailoring my thesis. I would also like to recognize Professor Marti Subrahmanyam for his assistance in selecting Professor Sundararajan as an adviser and for his guidance to our class throughout the semester on our participation in this program. Jessica Rosenzweig also deserves recognition for her facilitation of the program. I also want to thank all of the fellow Honors students for their help, support, and camaraderie throughout this intense yet incredibly rewarding experience. I would also like to thank Professor Sam Hui for connecting me with Jared Feldman, the CEO of Mashwork, a social media analytics agency. Meeting with Jared Feldman significantly influenced the focus of my project and helped me narrow its scope in a way to make the research impactful, so I would like to thank him as well. I would also like to thank Professor Anindya Ghose; I took his Social Media and Digital Marketing Analytics class last semester, and this class provided me with the skills and expertise necessary to complete the regression analysis for my project. Finally, I would like to thank my parents, Mari Corson and Robert Corson, for raising me in a tech-savvy environment that drove my interest and passion for this topic, and also for providing the emotional support to complete a successful undergraduate career at NYU Stern.

Executive Summary

Although many studies have evolved to include social media as a means for predicting demand or sales, few have ventured into the space of determining brand perception. Marketers find the need for determining and monitoring brand perception, as the brand is one of the company's largest yet most nebulous assets. The emergence of social media has changed how marketers understand that perception and also alters their approach to branded content and content about brands, particularly in the newest classifications of owned, earned and paid media. In the mid-20th century, marketers simply utilized push campaigns in one-way communications with consumers, but this new era of digital data has forced marketers to understand the two-way communication consumers now demand from brands.

My thesis tests whether or not user-generated content is more powerful than brand created content in shifting or directing consumer perceptions. In particular I focus on Instagram as a means for gauging sentiment and imagery, which is unique to the platform's content. Other studies have represented these ideas through textual analysis, so my analysis will incorporate

photos as a way to connect sentiment and perception. These understandings can help to create learnings or provide insights for how companies can better capitalize on or effectively react to such content outside of their control. Furthermore, my thesis connects brand perception to content as well as to social influence to create a comprehensive view of this perspective on understanding brand engagement.

Lewis Goldberg developed 5 human personality traits that for no matter for which sub-characteristics psychologists applied, results returned to these 5 traits. These 5 traits include Surgency, Agreeableness, Conscientiousness, Emotional Stability, and Culture. Jennifer Aaker's later study and application to brands developed updated criteria: Sincerity, Excitement, Competence, Sophistication, and Ruggedness. I used these five criteria as an essential classifier throughout my research.

Studying Instagram has several benefits. The content theoretically has more interest or meaning due to the fact that taking and uploading a photo as well as applying a filter takes more effort than simplying posting or tweeting a sentence. There is also an interesting potential between photography and brand perception due to the emotions evoked and interpreted. The network interactions also simplified my analysis, since users cannot share content but can only like and comment. Instagram is an emerging social and mobile platform, and using it as the basis for my research makes it relevant and impactful. Brands have also taken notice of the network, and many top brands have a presence on the platform.

I analyzed 5,000 photos hashtagged starbucks, dunkindonuts, or jambajuice that users uploaded over a 1 week period. I analyzed the variables of the number of followers for the user who took a given photo, the number of photos the user had taken on the platform, the likes and comments the photo received, the number of and associated tags, the location and the filter. This analysis determined the statistically significant positive and negative relationships between variables and likes, which are a proxy for engagement and understanding. All variables had a positive and statistically significant relationship with the number of likes with the exception of Starbucks who had a negative association for the number of hashtags. I also classified the filters along the personality traits based on descriptions of their effects to analyze the relationship between the filter and its impact on the branded content. Each brand's associations with filters aligned with their brand competencies in a statistically significant way.

I finally created a weighted index for "influence" in the dataset, although this is a loose and incomplete definition of the word. Starbucks' index subtracted the use of hashtags while the other two added it due to their positive relationship. These calculations found that Starbucks had a much higher score than the top three photos in the dataset, but Dunkin' Donuts and Jamba Juice had the opposite occur. The photos' alignment with the brands varied in interesting and meaningful ways. The word frequencies of associated tags in the dataset also demonstrated that users selected certain hashtags as additional descriptors that enhanced or added to the brand's personality in addition to the portrayal created by the highest scoring photos.

This study established a preliminary relationship between imagery, sentiment, and the impact of user-generated content. It demonstrated that these relationships must be analyzed independently by brand due to the unquantifiable intrinsic value of the brand. It also aligned with other research that proves the importance of influence, subject and situation in perpetuating value. Finally, the study also establishes some potential marketing implications as well as areas of future research, such as location, network search details, and the importance of the new @ tag feature on the platform.

Hypothesis

The premise of my research is that users post content with perceptions that may differ or vary from perceptions furthered by corporate marketing teams via traditional media. There is some entanglement of influence and perception in social media. It is the "lens" through which we view and measure user perception, but it is also a channel via which user perceptions are shaped. The broad questions that shape my research are: When is user generated content more or less powerful than brand created content in shifting or directing consumer perceptions? How can companies capitalize on or react to user generated content?

These questions drove me to my hypothesis: User generated content is more powerful than brand created content in shifting or directing consumer perceptions, and companies can effectively capitalize on or react to this user generated content.

My hypothesis remains relevant in the marketing world today because marketers have to decide how customers influencing one another affects how they engage with their customer base. Marketers can leverage the knowledge of influencers and brand advocates in certain networks to effectively interact with and deliver certain content or messaging to customers. For example, if they find a lot of users behaving in one way that remains consistent with their branding, they can work to amplify these efforts and engage the user base in perpetuating this meaningful participation. Studying Instagram as well also serves a relevant purpose, because its relatively new presence in the social space and its integration with Facebook, one of marketers' top social media platforms, drives need for greater understanding of its effects.

II. A Survey of Previous Literature

The Roots of Brand Personality and Influence on Consumer's Perceptions

One major aspect to attributing personality to brands includes "The Big Five", a set of traits as defined through research by Lewis Goldberg, a psychologist at the University of Oregon. Using Cattell's 35 variables, Goldberg determined definitive classifications: (I) Surgency (or Extraversion), (II) Agreeableness, (III) Conscientiousness (or Dependability), (IV) Emotional Stability (vs. Neuroticism), and (V) Culture (or Intellect and Openness)[1]. His researched confirmed this structure, reviewed the validity of such analysis, and considered additional factors. Overall, no matter which sub-characteristics psychologists apply or utilize in their studies, all personality traits essentially come back to these five characteristics.

This classification aides in the research of brand perception in the digital space greatly. Due to the constraints of sentiment analysis and questions of the quality of social data, data analysts can instead focus on the adjectives that fall within these categories and get an overall understanding of user perception. Furthermore, when considering user-generated content and imagery, simplifying a qualitative analysis of the emotions or personalities evoked to these five traits can provide a foundation for interpreting and classifying these images.

Understanding personality from a psychological perspective directly translates to how we study the personality of brands. Brand Personality takes the characteristics of a brand and puts them within the context of human traits, enabling consumers to identify with or aspire to be like their brand of choice[2]. Consumers can have this approach toward brands because they can apply these traits to a visualization of a person, and the stronger the brand identity, the longer-lasting these traits are in the consumer's mind. Furthermore, Aaker references the somewhat circular nature of brand personality; people associate certain personality traits with brands because they

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[1] Goldberg, Lewis R. "An Alternative "description of Personality": The Big-Five Factor Structure." *Journal of Personality and Social Psychology* 59.6 (1990): 1217.

[2] Dimensions of Brand Personality. Jennifer L. Aaker Journal of Marketing Research , Vol. 34, No. 3 (Aug., 1997), pp. 347. American Marketing Association. http://www.jstor.org/stable/3151897.

associate certain people with the brand and consequently their personality traits[3]. Demographic associations, such as gender, age, and class also helps consumers identify certain traits or characteristics as belonging to the brand.

Aaker's study helps provide a basis for measuring brand personality in the sense that she accounts for a variety of factors to develop a model that can work across a variety of brands. By having subjects in the study rate 114 traits for each brand on a Likert Scale, she has essentially developed a complex understanding of each brand similar to consumer's complex understanding of one another. These traits were then attributed to a new set of the "big five": Sincerity, Excitement, Competence, Sophistication, and Ruggedness. Aaker then ran a separate study as a confirmation of these traits and continued to find reliable results. Overall, this research demonstrates that three of her brand traits correspond with the traditional Big Five traits for humans (Agreeableness to Sincerity; Extroversion to Excitement; Conscientiousness to Competence) while two emerged as new traits (Sophistication and Ruggedness). One important observation is the difference in achievable versus aspirational elements of these traits[4]; Sophistication and Ruggedness do have a glamorous component to them that make them more difficult to attain as a human yet available for a brand who may be idealized.

Allen and Olson also consider the importance a brand narrative as opposed to simply a personality. Their research considers a deeper relationship between the observer and the brand, especially in associating certain characteristics with that brand. They argue that consumers view a personality on longevity of interactions, similarly to how someone would interact with a

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[3] Dimensions of Brand Personality. Jennifer L. Aaker Journal of Marketing Research , Vol. 34, No. 3 (Aug., 1997), pp. 348. American Marketing Association. http://www.jstor.org/stable/3151897

[4] Dimensions of Brand Personality. Jennifer L. Aaker Journal of Marketing Research , Vol. 34, No. 3 (Aug., 1997), pp. 353. American Marketing Association. http://www.jstor.org/stable/3151897

friend[5]. Consumers react positively to this approach because of their natural tendency to create and accept narrative, so marketers capitalize on this knowledge in the content they create for their brand.

In the digital era, the application of Brand Personality beyond perception has become increasingly relevant due to the blurred nature between human and brand communications. The difference between content produced by brands in social media and followers or advocates and the translation of advocates' personality to a brand may help develop its personality in a minimal yet impactful way. However, based on Aaker's research, the differences in brand personality dimensions of humans versus brands indicates that brand advocates cannot wholly and completely represent a brand image due to their inability to be perfect and idealized. This raises the question of whether or not our perceptions of brand personality can shift from these idealized classifications to a more human interpretation of brands.

In the statistical analysis of digital data of Instagram that will appear later in this paper, this notion of analyzing across hundreds of personality traits or emotional references is a bit harder to apply. Sentiment in social media presents a major challenge for data analysts due to the lack of clarity in a lot of the data. Thus, I will classifying the filters within these personality traits as a means to understand sentiment.

User Generated Content

One study of particular relevance to this analyze comes from research conducted by EURECOM in which they attempt to differentiate among different users in their influence of trends on a mobile photo application. The study defines different sets of users: trend spotters, who vote for cool items that eventually gain popularity, and trend makers, who upload popular

[5] Allen and Olson, as cited by Aaker, Jennifer and Susan Fournier. "A Brand as a Character, A Partner and a Person: Three Perspectives on the Question of Brand Personality." Advances in Consumer Research (Volume 22) 1395. Page 393.

content. The users take photos of "cool things" which other users may like, dislike or comment but cannot retweet or share. The application in the study also tracks specific tags and location. This research determined that more users vote on pictures than actually generate them and that there is a small group of users who generate most of the content. Furthermore, the study found more users voted positively than negatively.[6]

Additionally, this study also develops a methodology of considering diversity or narrowness of content. This research considered "upload diversity", "vote diversity" and "consumption diversity" in determining whether or not the most influential users had a narrow focus or posted specifically in one category[7]. The researchers also developed a useful table with acceptances and rejections of their various hypotheses:

Exhibit: Table 1. Their Hypotheses (✓:accept hypothesis; x:accept the alternative hypothesis; *:unknown)[8]

	Content	Result
Spotters vs. Typical	H1.1 Trend spotters are more active than typical users.	✓
	H1.2 Trend spotters tend to be more specialized than typical users in certain category of items.	X
	H1.2 Trend spotters attract more followers than typical users.	✓
Makers vs. Typical	H2.1 Trend makers are more active than typical users.	✓
	H2.2 Trend makers are more specialized than typical users in certain category of items.	X
	H2.3 Trend makers attract more followers than typical users.	✓
Spotters vs. Makers	H3.1 Trend makers upload content more often than trend spotters.	✓
	H3.2 Trend makers vote less often than spotters.	✓
	H3.3 Trend spotters upload more diverse content than trend makers.	*
	H3.4 Trend spotters vote less diverse content than trend makers.	X
	H3.5 Trend makers have more followers than trend spotters.	✓

There are key takeaways in what from this study applies to the research presented later in this document. Primarily, this study includes the variable of disliking a photo which does not

[6] Sha, Xiaolan, Daniele Quercia, Matteo Dell'Amicao, and Pietro Michiardi. "Trend Makers and Trend Spotters in a Mobile Application." *Leveraging a Social Network* (2013): n. p. 2. 23 Feb. 2013. Web.
[7] Sha, Xiaolan, Daniele Quercia, Matteo Dell'Amicao, and Pietro Michiardi. "Trend Makers and Trend Spotters in a Mobile Application." *Leveraging a Social Network* (2013): n. p. 5. 23 Feb. 2013. Web.
[8] Sha, Xiaolan, Daniele Quercia, Matteo Dell'Amicao, and Pietro Michiardi. "Trend Makers and Trend Spotters in a Mobile Application." *Leveraging a Social Network* (2013): n. p. 6. Feb. 2013. Web.

exist on Instagram. Secondly, there are distinct groups of users who influence the network and others who do not. Finally, the research used tags as a way to analyze content, a similar approach I will take in my analysis later.

Relevance of Network Influence

Marketers have always considered product or service influencers an important consideration for any marketing strategy or plan, as customer word-of-mouth can strongly drive awareness, trial, and repeat purchases. With the emergence of digital data, both marketers and data scientists now have found new and interesting ways to research influence among friends within a digital social network, which of course to a certain extent reflects a user's actual social network. Past researchers have taken a variety of both qualitative and quantitative approaches in identifying influential users in online social networks. An analysis by x reveals many different criteria for considering user influence. Most researchers attribute level of activity on a network and "whom one knows" more often than the knowledge or characteristics of that person as metrics of influence[9]. Furthermore, when considering user influence, researchers have also needed to consider the importance of the susceptibility of users to such influence; if an influencer has a strong network of people with questionable acceptance of their influence, such a misplaced dynamic could damage the value of their content or its influence. Aral and Walker determined in their research of Facebook varying degrees of characteristics that make certain pieces of a network more or less influential, such as age, marital status, and gender[10].

However, this article specifically excluded consideration of content-oriented sites, which is an important research distinction. A secondary distinction from past research and the

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[9] Probst, Florian, Laura Grosswiele, and Regina Plfeger. "Who Will Lead and Who Will Follow: Identifying Influential Users in Online Social Networks - A Critical Review and Future Research Directions." *University of Augsburg* (n.d.): n. p. 15. Web.

[10] Probst, Florian, Laura Grosswiele, and Regina Plfeger. "Who Will Lead and Who Will Follow: Identifying Influential Users in Online Social Networks - A Critical Review and Future Research Directions." *University of Augsburg* (n.d.): n. p. 22. Web.

Instagram analysis later provided considers that between influential and viral content. Viral content refers to that which essentially gains significant and momentum through user influence and rapid popularity; influential content faces a much less obvious understanding amongst users and researchers. While network research focuses more on the relationships between overall network dynamics and influence within user clusters, an approach to content influence must still consider what is actually being posted and propagated. Furthermore, another note to consider in spread is the positive or negative tone of the content; Berger and Milkman determined negative content had much greater virality than positive[11]. Overall, a later analysis of Instagram can determine whether or not these sentiments apply to the network and its content.

From a content marketing perspective, the observations regarding the level of influence based on different network characteristics could negatively impact how marketers evaluate their approach because in network dynamics, the actual content may be less relevant that who is actually propagating those ideas or identities. Furthermore, marketers must recognize the importance of connecting the demographic impact of network influence to a brand's target consumer to better evaluate the realistic dynamics of information spread from one influencer to their followers. Finally, in the new era of conversational and "pull" marketing, those analyzing their users' content on Instagram need to consider whether or not it provides a representative sample of users' satisfaction and dissatisfaction with its products or services.

III. Data and Methodology

Why Instagram?

For this particular project, I feel that Instagram is an excellent platform to analyze for several reasons. First, the content users create tends to have some sort of interest or meaning; the effort

[11] *Ibid.*

placed in taking a photo and selecting a filter means the user is much more engaged with their photographed subject than simply tweeting about a brand. Additionally, after conducting a preliminary sentiment analysis with an Excel plugin, it is clear that Twitter is a "wild wild west" of sorts, and understanding sentiment among tweets is rather difficult. I also recognized the strong potential to link photographic material to emotion, personality, and consequently brand perception. Because photographs have a visual appeal that can create a higher level of involvement both for the creator and for the viewer, the platform has a much stronger capabilility of driving and managing sentiment.

Additionally, the way users interact with Instagram makes it much simpler for analyzing the power of user-generated content. Users post content and other users either view it, like it, or comment on it. Because there is no sharing, lack of virality will make analyzing one users influence significantly easier.

Finally, Instagram is still a fairly young but popular social network, and there hasn't been too much analysis or recommendations for companies to use it. Many companies still haven't created their own accounts, so I feel research in this area would have more impact that doing research for Facebook or Twitter. As an active user of the platform myself, I understand its current usage and the user base and also recognize that the platform has definitely not completely leverage my ability to have a direct and personal engagement with brands.

Marketing on Instagram

As with any attempt at utilizing social networks for branding purposes, brands must understand the demographics of the network will help them link their strategies for usage to determine whether or not the network is an appropriate part of their branding initiatives, and if so, best engage their target audience. According to data from eMarketer, 13% of total internet users have Instagram accounts. The network also tends to skew younger, with nearly 30% 18-29 year old Internet users on the network[12]. With marketers having a strong preference for the 18-35 demographic, having a larger proportion of the demographic on this network certainly makes it more meaningful to marketers. Furthermore, based on internet users, the network has a slightly higher proportion of females but not enough to have them dominate the platform; by comparison, Pinterest has established a reputation among online communities as one which heavily skews female.

US Internet Users Who Use Instagram, by Demographic, Dec 2012
% of respondents in each group

Gender	
Female	16%
Male	10%
Race/ethnicity	
Black	23%
Hispanic	18%
White	11%
Age	
18-29	28%
30-49	14%
50-64	3%
65+	2%
Total	**13%**

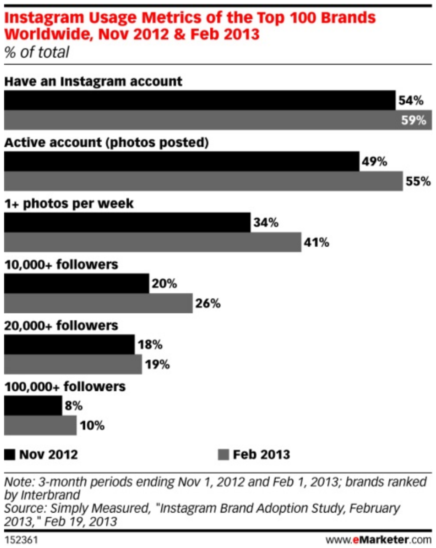
Note: n=1,802; read as saying 28% of internet users ages 18-29 use Instagram
Source: Pew Internet & American Life Project, "The Demographics of Social Media Users — 2012," Feb 14, 2013

152148 www.eMarketer.com

Furthermore, brands have taken notice of the attractiveness of this network. 59 of Interbrand's Top 100 brands have a brand Instagram account, 41 of whom post photos on a weekly basis[13]. However, the follower counts on this network for brands still remain

[12] US Internet Users Who Use Instagram, by Demographic, Dec 2012 (% of respondents in each group). February 14, 2013. eMarketer.
[13] Instagram Usage Metrics of the Top 100 Brands Worldwide, Nov 2012 & Feb 2013 (% of total). February 19, 2013. eMarketer.

relatively small. Only 10% of the brands have over 100,000 followers on a network of nearly 100 Million Active Users, capturing less than 1% of the total user base. Meanwhile, Facebook Pages in this same group of brands capture as much as 6% of the total user base.



Top 10 Brands Worldwide on Instagram, Ranked by Total Followers, Feb 2013

	Total followers	% change	Total posts	% change	Total engagement	% change
1. MTV	1,138,038	14%	794	-12%	1,984,583	-19%
2. Starbucks Coffee	1,074,986	23%	236	-26%	712,527	19%
3. Nike	879,166	67%	532	-52%	2,565,481	6%
4. Burberry	659,198	18%	752	-26%	1,021,468	15%
5. Tiffany & Co.	363,877	75%	255	13%	1,297,736	99%
6. Gucci	358,009	65%	158	50%	561,026	128%
7. Audi	327,083	90%	463	6%	1,867,209	52%
8. GE	133,726	-3%	186	-27%	28,189	-31%
9. Ralph Lauren	119,405	-	329	-	561,017	-
10. Adidas	119,397	103%	165	-4%	204,733	133%

Note: 3-month period ending Feb 1, 2013; brands ranked by Interbrand
Source: Simply Measured, "Instagram Brand Adoption Study, February 2013," Feb 19, 2013
152375 www.eMarketer.com

If we also look at an analysis of the brands on platforms, we fail to see a consistency between where stronger presence lies, and whether or not the brands have stronger engagement on which platform. This lack of consistency helps drive the questions regarding the importance of this new network. One question to raise is whether or not the follower count is relevant but rather the engagement with and impact on those who engage with the brands. And more specifically for Instagram, there is a relatively easy way to engage with a brand without actually officially following their account.

Exhibit: Brand Penetration: Instagram vs. Facebook

Brand	Instagram Followers	Penetration	Facebook Followers	Penetration	Stronger Presence
MTV	1,300,402	0.01300402	45,072,840	0.040975309	Facebook
Starbucks Coffee	1,229,188	0.01229188	34,502,157	0.031365597	Facebook
Nike	1,434,336	0.01434336	12,837,553	0.011670503	Instagram
Burberry	807,978	0.00807978	15,149,511	0.013772283	Facebook
Tiffany & Co.	564,310	0.0056431	4,162,726	0.003784296	Instagram
Gucci	587,489	0.00587489	10,770,350	0.009791227	Facebook
Audi	410,040	0.0041004	6,806,382	0.00618762	Facebook
GE	131,330	0.0013133	942,011	0.000856374	Instagram
Ralph Lauren	217,314	0.00217314	6,791,135	0.006173759	Facebook
Adidas	244,804	0.00244804	13,507,145	0.012279223	Facebook

Base number of Instagram of 100 million users (from Press Center);

Base number of Facebook Users of 1.1 billion users (from Facebook Q1 Results)

IV. The Data Set

In order to evaluate Instagram from a marketing perspective, I decided to focus on three fast beverage category brands, Starbucks, Dunkin' Donuts and Jamba Juice, for several reasons. First I felt there was enough inherent difference between these brands that the results would provide enough of a basis for comparison in the grand scheme of positioning; essentially, the brands were relatable but distinct. I also wanted to include a smaller beverage chain in my data set to provide some differences between relative network; my purpose was not to find the biggest, but to find the most engaging.

To acquire my dataset, I hired a developer to scrape Instagram for 5,000 photos during a one-week period where each brand was hashtagged. This means of study obviously has limitations, since some users may photograph brand content but may not tag it, which for the time being makes it relatively impossible to find. Alternatively, as we will see in my data peculiarities, just because the user uses a brand hashtag does not mean the photo is related to that content. However, for the purposes of this study, I found that using the brand hashtag was the best way to gather the content, as before my study there was no other means on the platform to tag brand content. For each photo, the data included the username of the user who took the photo, the number of followers the user has, the number of photos the user has taken on instagram, how many likes the photo received, how many comments the photo received, what were the other associated hashtags, how many hashtags there were, where the photo was taken, and which filter the user selected.

In order to effectively study the filters, I decided to group them into the different personality classifications from Aaker's study based on the descriptions of the filters and the effects they had on photos. This part of the study is where I obviously took a bit more creative liberty, but doing so helped to tie what the effect of filters, which are a strong point of differentiation for the Instagram platform, had on brand personality and perception. Most filters fell into Excitement, Sincerity, and Sophistication, with Hudson being the only filter I classified as ruggedness. I classified Normal (no filter) as Competence. For a list of my classifications, see Appendix A.

V. Data Set Analysis

Before I started doing any regressions, I felt it necessary to understand my datasets from a holistic perspective. Overall, each brand's users had a similar distribution of followers, peaking at 100-200 followers and then tapering off to a very small group that had over 2000 followers. This result aligns with the general assumption in both psychology and social networking that a person has approximately 150 friends. Additionally, most users selected to upload photos without a filter, while the top two filters were Amaro and Rise (which I will discuss later in my data peculiarities section). Across brands, the number of photos the users had taken also had a similar tail end effect of the followers; there was a large portion of users who had contributed under 200 photos to the platform, and a tail end going to 2000-4000 photos depending on the brand. This information demonstrates that there are a large portion of users who have fairly new interactions with the platform as well as a smaller network than many of the brands.

My first regression was on the relationship between various variables and the number of likes the photo had received, and I conducted this analysis separately for each brand. These variables included the number of photos the user who had taken the given photo had contributed to the platform, the number of followers the user who had taken the given photo had, the number of hashtags the user had included for the photo, and whether or not the photo used a filter. I selected a poisson regression for all variables except whether or not the user applied a filter, for which I used a probit regression. For all three brands, the number of photos and number of followers had a positive relationship with the number of likes the photo had received and were statistically significant at the 0.1% level For all three brands as well, generally whether or not the photo had a filter was statistically insignificant in relationship to the number of likes. The only difference in variable relationships was that for starbucks, the number of hashtags had a negative relationship with the number of likes, while for the other two brands it had a positive relationship. I will provide a possible explanation later when I discuss the "hashtag hackers".

Exhibit: Regression Coefficient Results. All results significant at 0.1%*

Brand	**Variable**	**Coefficient**
Starbucks	# of photos	0.001321***
	# of followers	0.0000358***
	# of hashtags	-0.0033699***
	Filter	-0.297072
Dunkin' Donuts	# of photos	0.00586***
	# of followers	0.0000555***
	# of hashtags	0.0409875***
	Filter	-0.141581
Jamba Juice	# of photos	0.0072471***
	# of followers	0.00000667***
	# of hashtags	0.0493693***
	Filter	-0.0723936

I then conducted a dummy variable poisson regression on the different filters as classified by personality and also came upon some interesting and significant results. I left out competence, or images with no filter, as the missing dummy variable, so all coefficients are in comparison to if the photo had not applied a filter but is categorized by the personality variable it would evoke.

For Starbucks, photos with Excitement or Sophistication filters were more likely to gain likes, while Sincerity was les likely to gain likes. These results align with Starbucks' positioning as a premium or aspirational brand. Dunkin' Donuts also had mostly negative results, which implies that photos without a filter or with an exciting filter were more likely to receive likes. This result aligns with Dunkin' Donuts' general positioning of Competence. Finally, Jamba Juice received all negative coefficients, again aligning it with Competence.

Exhibit: Regression Coefficient Results: Filter Personalities vs. Likes

Brand	**Variable**	**Coefficient**
Starbucks	Sincerity	-0.0630673***

	Excitement	0.2857395***
	Sophistication	0.0585101***
	Ruggedness	0.0642537**
Dunkin'	Sincerity	-0.3685632***
	Excitement	0.0212685**
	Sophistication	-0.1436558***
	Ruggedness	-0.4403573***
Jamba Juice	Sincerity	-0.3154586***
	Excitement	-0.4455576***
	Sophistication	-0.3118561***
	Ruggedness	-0.4002786***

**Significant at 1% level

***Significant at 0.1% level

VI. Weighted Index

In addition to running regressions on these variables, I created an index for each of the brands. Calculating this index would determine in the dataset whether or not in this 1-week period the brand or the users had more influence. By no means is this the best or most complete index, and classifying it for influence of course is a bit of a stretch and comes with many connotations in the social media and digital marketing world, but for purposes of simplicity, I will consider it an influence index.

Starbucks

For Starbucks, I created the following index:

$$\frac{Likes \times 1 + Comments \times 2 + \frac{\#\ of\ Photos}{Average\ \#\ of\ Photos} - \frac{Hashtags}{Average\ \#\ of\ Hashtags}}{Followers}$$

In this index, I weighted comments twice as much as likes since comments indicate a more involved engagement with the brand comment then a simple double-tap. I also incorporated the number of photos the user had taken over the average number of photos the users in the dataset had taken, so as to create proxy for involvement and activity on the platform. I subtracted the hashtag number, since the prior regression showed a negative influence for Starbucks. I then also divided that all by the number of followers in order to weigh the relative impact for each user. For instance, a user who has 400 followers and gets 200 likes has more impact on their network than a user with 400 followers and 100 likes. I calculated this for each photo in my dataset and also for Starbucks's most popular photo in the same period of time. These calculations resulted in the following scores:

User	Score
starbucks	32.02516
ratchetqueen14	13.358648
zafertemel	11.3234918
modernmilf	8.04165511

Thus, Starbucks had a much stronger index score than even those of its top followers. This essentially implies that Starbucks has more influence through its generated content than users do through their user-generated content.

I then classified each of these photos by the brand personality attributes plus the photos that had been most liked and most commented on (in this case, it was the same photo). Starbucks' photo aligned with sophistication, as it portrayed a fancy foam drink as it was being created. Ratchetqueen14's photo aligned with Sophistication, as it portrayed Starbucks products with classy literature. Zafertemel's photo, although seemingly unrelated to Starbucks, had a slight element of Ruggedness, something that aligns with the filter regression results from earlier. Modernmilf's photo, in which the user has repurposed the Starbucks plastic container to hold paint, represents Starbucks' alignment on the trait of Excitement. The most popular photo, a hand with a sparkly fingernail and an engagement ring holding a Starbucks cup, also represents Sophistication. For photos, see Appendix E.

The other hashtags associated with Starbucks has some of the most interesting findings of the three brands. First off, coffee has one of the strongest presences within the dataset. Secondly, the word “love” has a particularly strong presence in the dataset. Users of Starbucks clearly have a strong affiliation toward the product if they are categorically using love as a descriptor. Lastly, neither Dunkin’ Donuts nor Jamba Juice appear in the dataset of associated hashtags, while Starbucks appears in the other two datasets. Thus, users in the Instagram network are comparing these brands to Starbucks, but not Starbucks to these brands. Since Dunkin’ Donuts and Jamba Juice are not comparing themselves directly in any of their marketing campaigns to Starbucks, it is clear that this insight of brand perception comparison is driven from the network and not from the corporate identity. For the full visualization, See Appendix F.

Finally, I compared these filter results with the associated tags’ frequency and also classified the terms along the personality traits to create a comparison between the visual and the descriptive. These results demonstrated a strong description presence of Excitement, which differs from our sample of photos which has a much stronger presence of Sophistication. Thus, the users are utilizing the hashtags as an additional, secondary descriptor for how they feel about the brand. Also note that I did not classify the “instagood” hashtag. Users incorporate this hashtag to gain more visibility for their photo across the platform, so it does not associate with any particular dimension.

Exhibit: Frequency Table, Starbucks

Frequency	Word	Brand Dimension
833	coffee	Competence
599	love	Excitement
366	like	Excitement
345	yum	Excitement
326	follow	Sincerity
321	yummy	Excitement
228	instagood	-
196	cute	Excitement
191	friday	Excitement
183	delicious	Excitement

Dunkin' Donuts

For Dunkin' Donuts and Jamba Juice, I created the following index:

$$\frac{Likes \ \times 1 + Comments \ \times 2 + \dfrac{\#\ of\ Photos}{Average\ \#\ of\ Photos} + \dfrac{Hashtags}{Average\ \#\ of\ Hashtags}}{Followers}$$

This index is identical to the Starbucks index, except that I added the hashtag number, since the prior regression showed a positive influence for these two brands. These calculations resulted in the following scores:

User	Score
dunkindonuts	1.879609
___delish	6.045330779
gadred	3.062373941
beautificational	2.486335216

Thus, the users had a much stronger index score than Dunkin' Donuts by a significant amount. This essentially implies that the users have more influence through their generated content than the brand does through its generated content.

I again classified each of these photos by the brand personality attributes plus the photos that had been most liked and most commented on (in this case, it was the same photo). All photos in the dataset aligned with Competence. All photos represented the coffee or donut products the company offers. Thus, although the users have more “influence” than the brand, they are perpetuating the same brand personality as the brand is. For photos, see Appendix G.

Finally, the other hashtags used with the Dunkin’ Donuts hashtag helps to paint a picture with the brand associations users in the Instagram network are creating. Not surprisingly, coffee has the strongest presence, as does donut and donuts. Additionally, we don’t see too many words that would be outside the realm of what Dunkin’ Donuts would want for its own branding. Again, these ideas align to their positioning as Competence. For the full visualization, See Appendix H.

In a similar comparison for the tags’ frequency, Competence again appeared as a frequent classification for the associated tag, although Excitement through terms like yum, yummy, and love, did add additional dimension to the product. Thus, the users have recognized the strong positioning on Competence but have used the hashtags as a secondary decscriptor to represent the Excitement associated with the product.

Exhibit: Frequency Table, Dunkin’ Donuts

Frequency	**Word**	**Brand Dimension**
979	coffee	Competence
492	donuts	Competence
406	yum	Excitement
385	yummy	Excitement
355	dd	Competence
338	icedcoffee	Competence
335	love	Excitement
330	food	Competence
301	dunkin	Competence
238	breakfast	Competence

Jamba Juice

The index calculations resulted in the following scores:

Brand	Score
Jamba Juice	0.775682
sopy_c	0.979601
losangelespart2	0.976903
vran1016	0.902949

Thus, the users had a much stronger index score than Jamba Juice, although the difference is much less pronounced than for Dunkin' Donuts. This still essentially implies that the users have more influence through their generated content than the brand does through its generated content. For photos, see Appendix I.

The photo classifications for Jamba Juice did not align with one or two particular traits, indicating a lack of strong perception of the brand by users. Jamba Juice's most popular photo aligned along competence as a photo demonstrating product variety, the other data points lacked consistency. User photos fell along Competence, Ruggedness, Sincerity; the most liked photo aligned with Excitement, while the most commented on photo aligned with Sincerity. Thus, the only trait missing from these top photos is Sophistication, which Jamba Juice did not infuse into its follower base.

Finally, the other hashtags used with the Jamba Juice hashtag has some differences with that of Dunkin' Donuts. First, product ingredients appear more frequently than that in the Dunkin' Donuts set. Additionally, there is a greater distribution of words hashtagged less often, while the Dunkin' Donuts dataset is significantly more concentrated. This disparity could indicate that the user base on Instagram has a much less clear understanding of what the Jamba Juice brand represents compared to Dunkin' Donuts. Contrarily, it could also mean that each user has a stronger sense of individuality in how they define their relationship with the brand.

Finally, another interesting point which I will investigate later is the appearance of #starbucks in both dataset for Dunkin' Donuts. Users in the network are clearly making comparisons between these different brands, perhaps since it is more reputable than these beverage brands. For visualization, see Appendix J.

The hashtags perhaps tell a clearer story for the brand. Most hashtags aligned along Competence or Excitement, which does reflect a potential personality. However, seeing as Jamba Juice is a smaller and still relatively new entrant to the market compared to the other two competitors, both the brand and the user base still may need a further clarification and understanding of the brand's personality before a strong perception on either end emerges.

Exhibit: Frequency Table, Jamba Juice

Frequency	Word	Brand Dimension
371	smoothie	Competence
270	yummy	Excitement
249	yum	Excitement
201	healthy	Sincerity
168	jamba	Competence
166	love	Excitement
135	delicious	Excitement
126	juice	Competence
125	instagood	-
108	mango	Competence

Brand Results

Overall, based on the above results, the Starbucks brand has more influence through its content than the users do, but for Dunkin' Donuts and Jamba Juice, the opposite holds true. Starbucks has most successfully popularized on the personality trait of Sophistication, while Dunkin' Donuts has done so on Competence. Jamba Juice, as a newer entrant to the market, is less defined by itself and by its users.

VII. Data Peculiarities

Filter Usage

For all of the brands in the fast beverage category, the Filter Usage rates aligned in a surprisingly interesting way. No filter constituted between 30% of the photos for each brand, while; Compared to Instagram as a whole, this rate is a greater usage of filters, since generally 43% of photos are taken without a filter. Users also chose Amaro and Rise over twice as much as the average rate on Instagram as whole, which is around 4%[14]. Amaro and Rise both fall into the Excitement personality classification; Amaro as a filter creates a "dodged center, slight exposure" in which the effect adds more light (See Appendix A). Rise as a filter creates a "slight exposure, warm temperature, yellow tint" in which the effect adds a golden glow. The use of these filters indicates that the overall user base engaged with the fast beverage category finds it meaningful to add a slight exposure and brighten the photos.

Exhibit: Filter Usage Rate

Brand	Filter	Personality	Filter Usage Rate	Instagram Average
Dunkin' Donuts	Amaro	Excitement	10%	4%
	Rise	Excitement	8%	4%
Jamba Juice	Amaro	Excitement	14%	4%
	Rise	Excitement	8%	4%
Starbucks	Amaro	Excitement	13%	4%
	Rise	Excitement	8%	4%

Location: A Jamba Juice Case Study

Overall for the data set, 70-80% of the photos did not include a location for the photos, and the distribution of locations looks pretty uniform to the distribution of Jamba Juice retailers across the world.

[14] Mlot, Stephanie. "Infographic: What Your Instagram Filters Say About You." *Infographic: What Your Instagram Filters Say About You | News & Opinion | PCMag.com*. PCMAG, 29 Mar. 2013. Web. 13 May 2013. <http://www.pcmag.com/article2/0,2817,2417252,00.asp>.

Jamba Juice also had slightly different data results compared to the other brands. Its international locations provide a particularly interesting insight; despite only having 8 Jamba Juice locations, the Philippines accounted for 38 photos in the sample dataset. Ontario also has 8 Jamba Juice locations, but only has 3 photos. This disparity in the data tells us that perhaps certain clusters of users in the offline network have an overall stronger influence on Instagram for this brand.

Furthermore, I noticed a particularly large cluster around Santa Monica, CA. Santa Monica has approximately 18 Jamba Juice locations but 150 data points, a much higher proportion than any other city and post ratio in the set. Upon further investigation, this datapoint revealed that Jamba Juice had partnered on the Fit Trends Expo on April 25, 2013[15]. With 150 different photos referencing Jamba Juice in this time frame and location yet nowhere else providing the same impact, it is clear that Jamba Juice event influenced the Instagram network.

Hashtag Hijackers

One observation I made in my dataset was recognizing that some users appeared in the dataset frequently and also had a large number of associated hashtags with the photo. Upon further analysis, I have coined these particular users as “hashtag hijackers”: users who incorporate the brand hashtag as a way to gain personal recognition as they post content completely irrelevant to the brand.

For Dunkin’ Donuts, 29 of the photos in the dataset come from user fahadalguwaiz, a student at Worcester State University[16], and 21 come from malotaibi10, another user in the Boston area. However, none of the photos he took actually include anything remotely related to

[15] "Jamba Juice FiTrends Fitness Trends Expo 2013 (Photos)." *Examiner.com*. N.p., 29 Apr. 2013. Web. 13 May 2013. <http://www.examiner.com/article/jamba-juice-fitness-trends-expo-2013>.
[16] "Instagram." *Instagram*. N.p., n.d. Web. 13 May 2013. <http://instagram.com/fahadalguwaiz>.

Dunkin' Donuts. He also used a series of unrelated hashtags, "#worcester #Usa #ksa #cold #uea #weather #photo #تصويري #السعودية #الرياض.#الخليج #الكويت #انا #دبي #followme #الخبر #الدمام #curly. #dunkindonuts #good_morning #yellow #edmonds #engineer #vaper #amazing #food #20likes #2013 #2012 #photooftheday". Presumably, this user is actually leveraging the Dunkin' Donuts brand to gain more popularity and is in fact using the brand's influence for his personal benefit. Additionally, Boston has a strong retail presence of Dunkin' Donuts, so these two users could be looking to engage locally by way of using this hashtag.

Starbucks also unfortunately fails to avoid the plight of hashtag hijackers despite having one of the most reputable brands among marketers and consumers, it. User daisymckenzie contributes 48 of the photos to the dataset through the user of her hashtag series: "flat,drunk,instalove,sunny,hair,summer,starbucks,follow,abercrombie,hipbones,like,brilliant,highfashion,iphone,pretty,instalike,hollister,model,tanned," and none of her photos seem to relate to Starbucks. A second source of hashtag hacking comes from user lllidi, who posts 23 photos with the series "cute,sketch,fashion,love,truestory,summer,color,unicorns,sweets,street,starbucks,delicious,wedding,goodworlds,miss,school,hashtags,srry,wish,likeback,glasses,bow,um,food,train,forest,s4s,lovely,adorable,l4l,". One interesting observation comes from lllidi's Instagram profile[17], where almost all of her photos are in fact of herself, also known in the digital world as a "selfie." However, lllidi fails to use the #selfie hashtag in any of these photos. Perhaps her use of #starbucks contains an aspirational element to it.

VIII. Conclusions and Key Takeaways, Recommendations, and Further Questions

[17] "Instagram." *Instagram*. N.p., n.d. Web. 13 May 2013. <http://instagram.com/lllidi>.

Conclusions and Key Takeaways

My analysis on Instagram is one of the first studies establishing a relationship between the impact of user-generated brand content and the "sentiment" expressed by users both verbally (hashtags) and visually (filters). Most studies regarding social media have focused on forecasting for sales and demand, but few have ventured into the territory of recognizing personality.

This research also demonstrates that certain variables and the user response has different results for different brands, and many of the explanations for these differences emerge from the qualitative understanding of the brand as opposed to a purely quantitative driven explanation. It also remains consistent with recent findings that the influence of people depends on the context, the product in question and the situation. Finally, this research suggests that there are social media specific features that need attention and that go beyond typical variables like timing, location and reach.

Recommendations

Based on more of these findings from the analysis in the dataset, brand marketers at these three beverage companies can learn a few things going forward to improve their brand identity on Instagram and better recognize the influence of user-generated content.

1. **Use offline engagement to drive online behavior:** as we saw in the Jamba Juice example, having an offline event drove significant usage of #jambajuice and thus pictures and branded Jamba Juice content being posted in the Santa Monica area. These types of events create a surge of influence that directly translates. Marketers then can study the behavior of a control group (Instagrams in areas without events) to the experiment to find out what new impressions they can make on the userbase in that area.

2. **Use brightening filters:** Users in this category tend to utilize the Amaro and Rise filters more than twice the network as a whole does. If the brands want to represent themselves in a way that reflects how their Instagram communities define them, they should apply these filters to the branded images they post.
3. **Use Filters With a Positive Association:** Each brand had a positive or negative association as compared with no filter, so brands should recognize this analysis and incorporate the findings accordingly for their own branded content.
4. **Discount users with too many hashtags in data analysis:** as we saw from the hashtag hackers on Dunkin' Donuts and Starbucks, some users are leveraging the brand for their own personal awareness, so I recommend that brands create a threshold for how many hashtags in a photo about their product discount a user's datapoint. These users posted 20 or more hashtags, so it might be wise to use that as a basis.
5. **Drive users to @ tag instead of #:** Instagram just recently launched a feature called "Photos of You" where users can tag other users in a photo, similar to that of Facebook[18]. This feature will enable brands to select which user photos to display in their user-generated tab; the brands can in fact leverage the user-generated content in a way that represents their brand how they may like it to be portrayed. Furthermore, this feature will help to deter some of the usage of hashtag hackers who don't necessarily take photos with the intent to represent or incorporate the brand.
6. **Encourage users to tag their location:** Given the nature of geolocation data and the presence of Foursquare since 2009, it was a bit surprising to see that nearly 4/5th of the network did not include a location in their photo, especially considering overall the distribution of photos largely matched that of the retail outlets. These brands can easily start

[18] (http://www.entrepreneur.com/article/226572).

encouraging users to tag their location when they upload a photo by displaying an in-store sign to remind them. They could also run contests locally where users who tag their uploads with the retailer from which they purchased and the managers at each of those locations picks a winning photograph to be printed and displayed as art in the store. This type of contest would mirror the idea of offline engagement at a broad scale and help brands get more accurate data. Finally, the brands would benefit with the residual effect of users becoming accustomed to tagging their location.

7. **Capitalize on user-generated hashtags**: Brands ultimate goal can be to integrate better into the digital community and drive their personality rather than simply their logo or icon, so recognizing the influence of its community and partaking in its conversation will truly drive authenticity. In all three datasets, #foodporn showed up as a consistent topic hashtag. These brands could first start using this hashtag on their own branded content to attempt to blend into the larger community of foodies and food aficionados on Instagram. They could also attempt to mobilize their followers by requesting that they use this hashtag – again, either in-store or via their corporate Instagram account.

Further Research

However, this study just covers the very basics for understanding brand interactions on Instagram, and several questions for future researchers in this discipline include the following:

1. Completing a more systematic empirical study, perhaps based on a field experiment or randomized trials
2. Completing a deeper analysis of the impact of location
3. Investigating a deeper understanding of how hashtags play a role

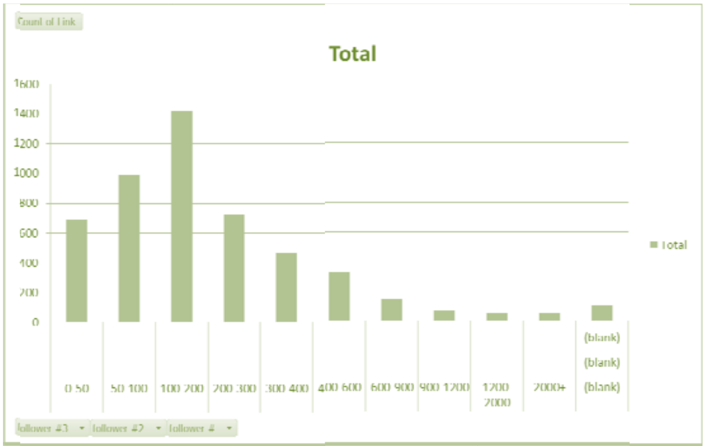
4. Understanding Network Search Details – users like photos of users they do not follow, so what are the dynamics associated with this behavior?
5. Integrating how the brands are interacting with users
6. Gathering more information and analysis on what brands know and are doing
7. Researching the impact of @ tagging, a newly added feature to the platform

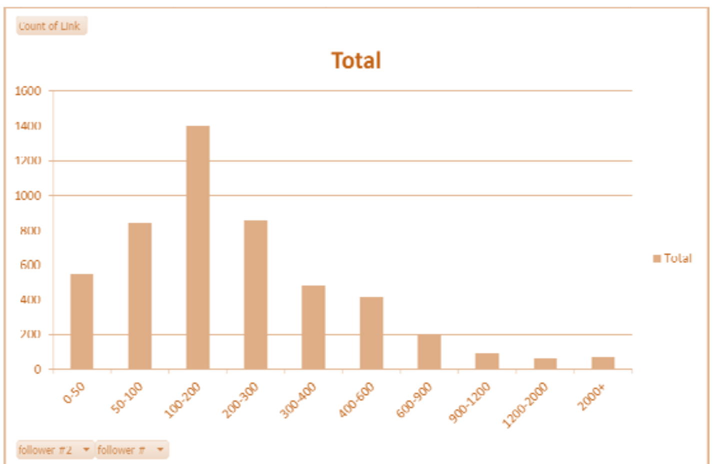
IX. Appendix

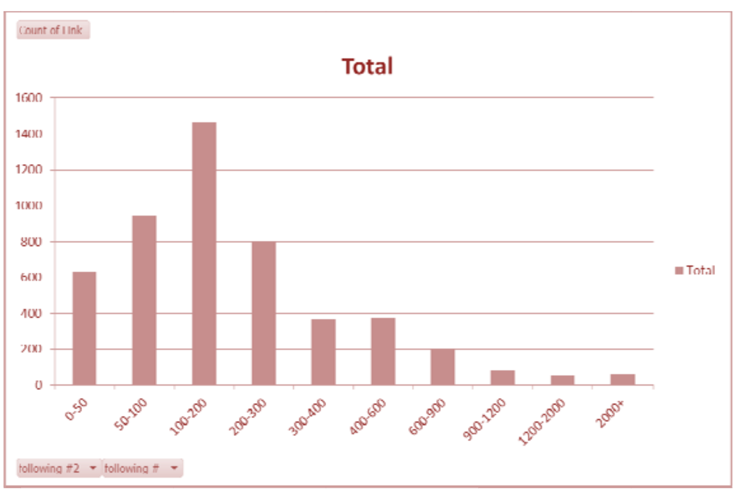
A. Filter Sentiments

Filter	Effect	Sentiment
1977	Rosy tones and cottony exposure	Sincerity
Amaro	The increased exposure seems to add more light, which oddly enough, can often make a photo appear harsh.	Excitement
Brannan	Brannan richens deep colors while softening neutrals, adding a sepia-like effect to your photos à la 19th century.	Sophistication
Early Bird	Old western photos; golden-red tones invoke past times, while the vignette effect retains drama.	Sincerity
Hefe	adds a vibrant yet cozy layer to your photos.	Excitement
Hudson	alters the light in your photo, making it appear icy.	Ruggedness
Inkwell	Black and White	Sophistication
Kelvin	adds a late afternoon-y glow.	Excitement
Lo-Fi	adds instantly rich colors and strong shadows.	Excitement
Mayfair	warm pink tone, subtle vignetting that brightens the center of the photograph, and a thin black border	Sincerity
Nashville	pleasant, pastel tint to your photo	Sincerity
Rise	adds a golden glow, which paints any picture in a softer, more forgiving light.	Sincerity
Sierra	cloudy quality to a photo	Sincerity
Sutro	Sutro adds a sinister tone to nearly every photo, combining both richness and Gothicism.	Sophistication
toaster	adding an aged, burnt quality to your images.	Excitement
Valencia	Faded quality without completely washing out color.	Sophistication
Walden	Imbues a pleasant, quaint light on photos, especially those containing lots of light.	Sincerity
Willow	monochrome filter with subtle purple tones and a translucent glowing white border	Sophistication
X-Pro II	a juicy pop to colors, while its vignette edges give the appearance of Photoshop technique.	Excitement

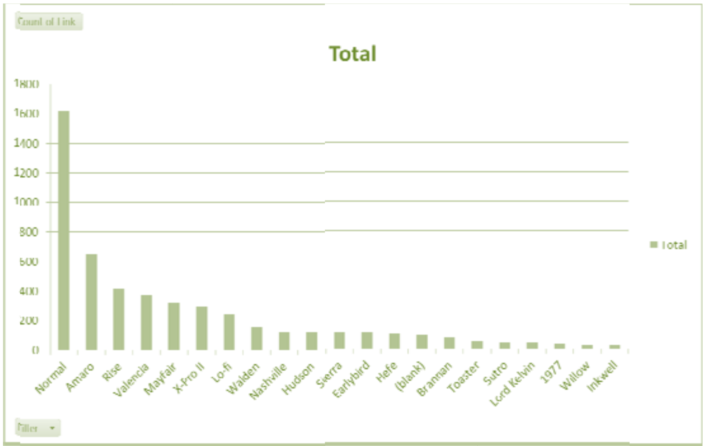
B. Distribution of Followers (Green = Starbucks, Orange = Dunkin' Donuts, Pink = Jamba Juice)

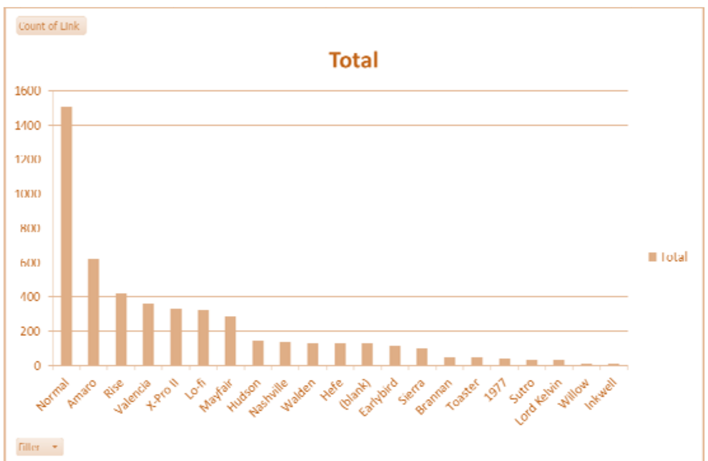


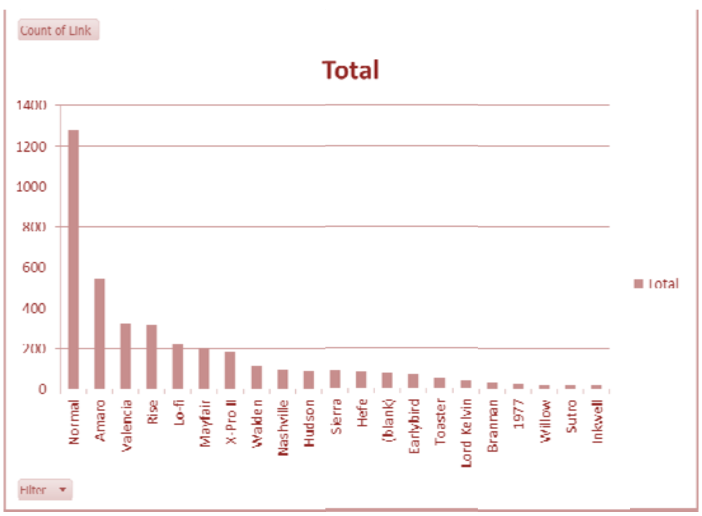




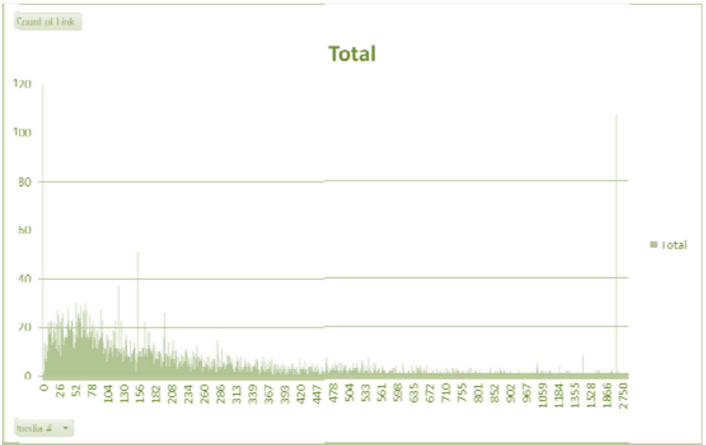
C. Filter Usage

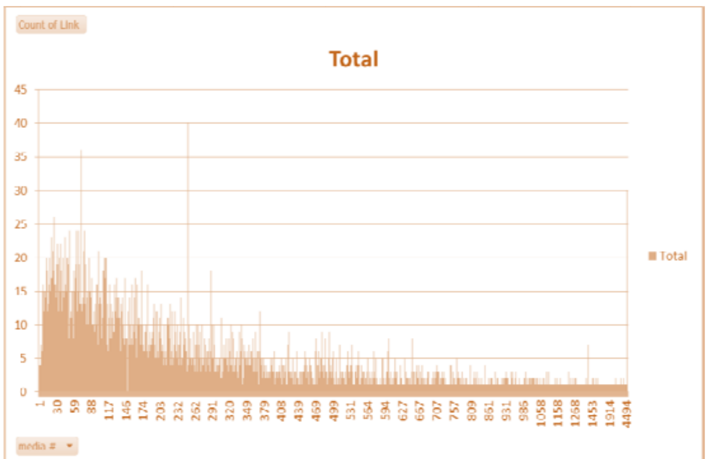


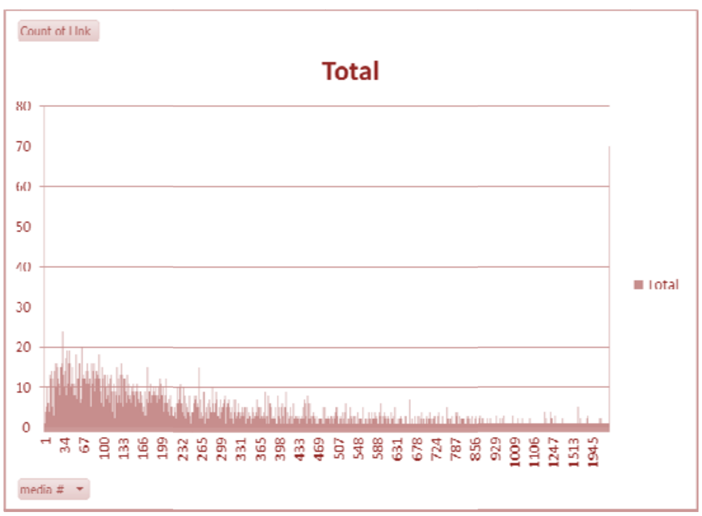




D. Distribution of # of Photos by User



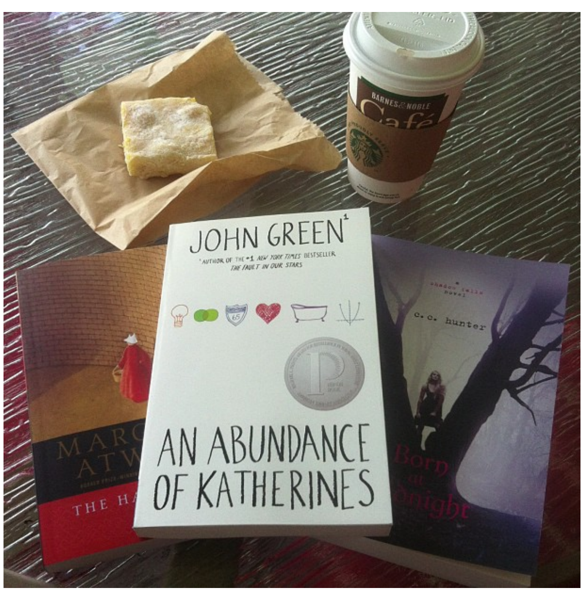




E. Starbucks Photos

Starbucks: Sophistication

Starbucks User 1: Sophistication



Starbucks User 2: Ruggedness

Starbucks User 3: Excitement

Starbucks Most Commented on and Liked: Sophistication

F. Starbucks World Cloud

G. Dunkin' Donuts Photos

Dunkin' Donuts: Competence

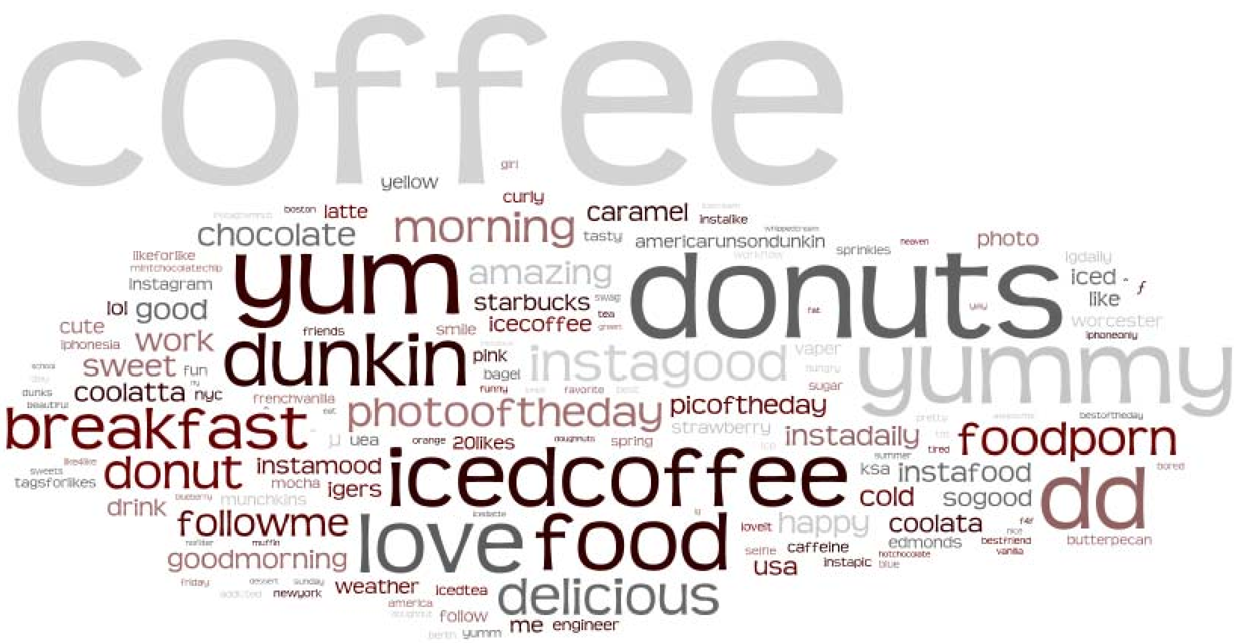
Dunkin' Donuts User 1: Competence

Dunkin' Donuts User 2: Competence

Dunkin' Donuts User 3: Competence

Dunkin' Donuts Most Liked and Commented On: Competence

H. Dunkin' Donuts Word Cloud



I. Jamba Juice Photos

Jamba Juice: Competence

Jamba Juice User 1: Competence

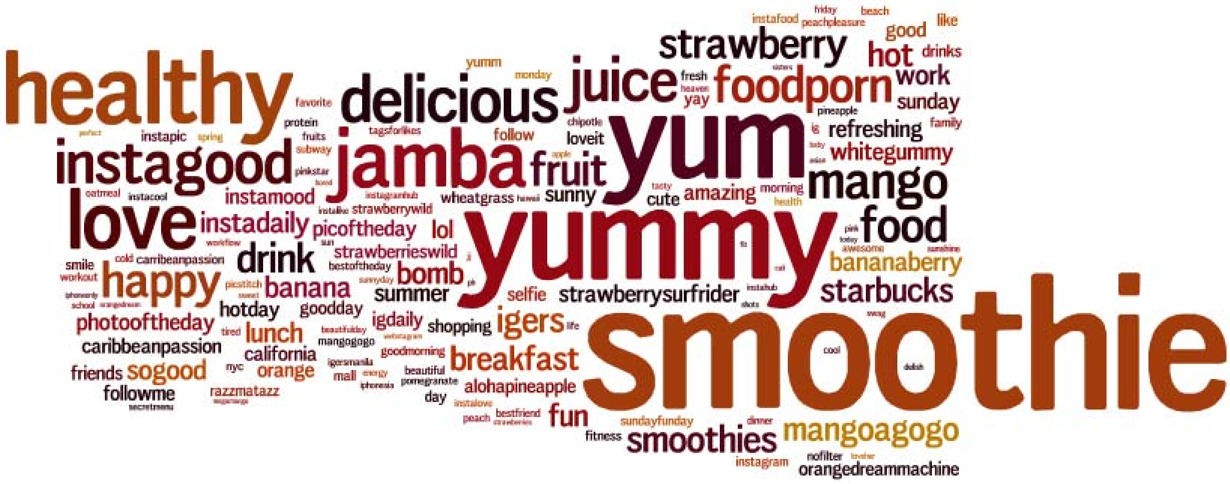
Jamba Juice User 2: Ruggedness

Jamba Juice User 3: Sincerity

Jamba Juice Most Liked: Excitement

Jamba Juice Most Commented On: Sincerity

J. Jamba Juice Word Cloud


healthy
delicious
juice
strawberry
hot
foodporn
work
sunday
yum
instagood
jamba
fruit
mango
refreshing
whitegummy
love
instadaily
picoftheday
yummy
food
drink
happy
banana
bomb
bananaberry
starbucks
smoothie
summer
strawberrysurfrider
strawberrieswild
photooftheday
hotday
goodday
igers
igdaily
shopping
selfie
lunch
caribbeanpassion
california
breakfast
friends
sogood
orange
alohapineapple
followme
razzmatazz
fun
smoothies
mangoagogo
orangedreammachine
instamood
amazing
cute
sunny
wheatgrass
loveit
instapic
lol
good
like
drinks
follow
fresh
yay
instafood
family
strawberrywild
cool
day
fitness
nofilter
instagram