What We Instagram: A First Analysis of Instagram Photo Content and User Types

Yuheng Hu   Lydia Manikonda   Subbarao Kambhampati
Department of Computer Science, Arizona State University, Tempe AZ 85281
{yuhenghu, lmanikon, rao}@asu.edu

Abstract

Instagram is a relatively new form of communication where users can easily share their updates by taking photos and tweaking them using filters. It has seen rapid growth in the number of users as well as uploads since it was launched in October 2010. In spite of the fact that it is the most popular photo capturing and sharing application, it has attracted relatively less attention from the research community. In this paper, we present both qualitative and quantitative analysis on Instagram. We use computer vision techniques to examine the photo content. Based on that, we identify the different types of active users on Instagram using clustering. Our results reveal several insights about Instagram which were never studied before, that include: 1) Eight popular photos categories, 2) Five distinct types of Instagram users in terms of their posted photos, and 3) A user's audience (number of followers) is independent of his/her shared photos on Instagram. To our knowledge, this is the first in-depth study of content and users on Instagram.

1 Introduction

Instagram, a mobile photo (and video) capturing and sharing service, has quickly emerged as a new medium in spotlight in the recent years. It provides users an instantaneous way to capture and share their life moments with friends through a series of (filter manipulated) pictures and videos. Since its launch in October 2010, it has attracted more than 150 million active users, with an average of 55 million photos uploaded by users per day, and more than 16 billion photos shared so far (Instagram 2013). The extraordinary success of Instagram corroborates the recent Pew report which states that photos and videos have become the key social currencies online (Rainie, Brenner, and Purcell 2012).

Despite its popularity, to date, little research has been focused on Instagram[1]. Fundamental and critical questions such as *What types of photos and videos do people usually post on Instagram?*, *What are the differences between users in terms of the their posted photos?*, and *How are these differences between users's photos related to other user characteristics, such as the number of followers?* remain open and untouched. We advocate that Instagram deserves attention from the research community that is comparable to the attention given to Twitter and other social media platforms (Naaman, Boase, and Lai 2010; Ellison and others 2007). Having a deep understanding of Instagram is important because it will help us gain deep insights about social, cultural and environmental issues about people's activities (through the lens of their photos). After all, a picture is worth a thousand words (in contrast, Twitter is mainly a text-based communication platform).

To address the gap, in this exploratory study, we aim to acquire an initial understanding of the type of photos shared by individuals on Instagram. To this end, we first crawl a large collection of photos and user profiles using Instagram API. Next, with the help of computer vision techniques and human coders, we conduct both quantitative and qualitative analysis to examine the activity of users on Instagram. Based on our analysis, several insights about Instagram photos and users are revealed. First, we find that Instagram photos can be roughly categorized into eight types based on their content: self-portraits, friends, activities, captioned photos (pictures with embedded text), food, gadgets, fashion, and pets, where the first six types are much more popular. Furthermore, we discover that there exist five distinct types of users based on the photos they posted. Lastly, we find that there are no strong correlations between different types of users and their characteristics (e.g., number of followers). This indicates that the size of a user's audience (followers) is independent of his/her shared photos on Instagram.

To the best of our knowledge, we believe this is the first paper to conduct a deep analysis of photo content and user activities and types on Instagram. In summary, the main contributions of this paper are:

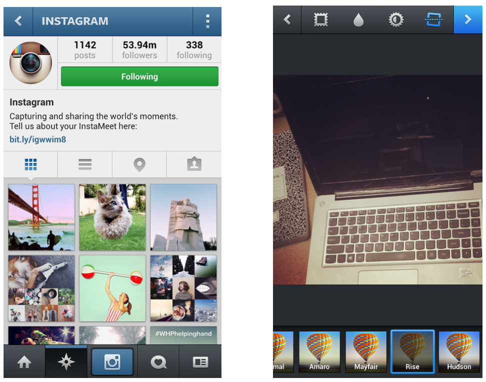
- A characterization of the content of photos shared on Instagram.
- An examination of how the content of photos is related to user types and characteristics.

2 Background

Instagram (Fig. 1) is a popular photo (video) capturing and sharing mobile application, with more than 150 million of

[1]We are aware of the small section of research on Instagram. Among the handful ones, McCune investigated people's motivations of using Instagram through a survey study of 23 Instagram users (McCune 2011). On the other hand, researchers have applied visualization and cultural analytics on Instagram photos from different cities in the world to trace their social and cultural differences (Hochman and Manovich 2013; Silva et al. 2013)

registered users since its launch in October 2010. It offers its users a unique way to post pictures and videos using their smartphones, apply different manipulation tools – 16 filters – in order to transform the appearance of an image, and share them instantly on multiple platforms (e.g., Twitter) in addition to the user's Instagram page. It also allows users to add captions, hashtags using the # symbol to describe the pictures and videos, and tag or mention other users by using the @ symbol (which effectively creates a link from their posts to the referenced user's account) before posting them.



(a) **(b)**

Figure 1: *Interfaces of Instagram. (a) Instagram app homepage, (b) Transforming a photo using filters*

In addition to its photo capturing and manipulation functions, Instagram also provides similar social connectivity as Twitter that allows a user to follow any number of other users, called "friends". On the other hand, the users following a Instagram user are called "followers". Instagram's social network is asymmetric, meaning that if a user *A* follows *B*, *B* need not follow *A* back. Besides, users can set their privacy preferences such that their posted photos and videos are available only to the user's followers that requires approval from the user to be his/her follower. By default, their images and videos are public which means they are visible to anyone using Instagram app or Instagram website. Users consume photos and videos mostly by viewing a core page showing a "stream" of the latest photos and videos from all their friends, listed in reverse chronological order. They can also favorite or comment on these posts. Such actions will appear in referenced user's "Updates" page so that users can keep track of "likes" and comments about their posts. Given these functions, we regard Instagram as a kind of *social awareness stream* (Naaman, Boase, and Lai 2010) like other social media platforms such as Facebook and Twitter.

3 Approach

Our analysis based on the Instagram data collected using the Instagram API, is a qualitative categorization of Instagram photos; and a quantitative examination of users' characteristics with respect to their photos. The data includes profile information, photos, captions and tags associated with photos, and users' social network that includes friends and followers. Below, we first provide details about the dataset we used, and later discuss how we develop a coding scheme for categorizing the photos and the coding process.

3.1 Data Collection Methodology

To obtain a random sample of Instagram users and retrieve their public photos, we first got the IDs of users who had media (photos or videos) that appeared on Instagram's public timeline, which displays a subset of Instagram media that was most popular at the moment. This process resulted in a set of 37 unique users. By careful examination of each user in this set, we found that these users were mostly celebrities (which may explain why their posts were popular). We then crawled the IDs of both their followers and friends, and later merged these two lists to form one unified list that contained 95,343 unique seed users. Next, we built a random sample of *regular active* Instagram users using this seed user list.

Specifically, we operationalized the notion of regular active users as those who are 1) not organizations, brands, or spammers, and 2) had at least 30 friends, 30 followers, and had posted at least 60 photos.[2] In practice, we found 13,951 users (14.6% of the seed users) who *satisfied* those criteria, out of which we randomly selected 50 users and downloaded their profiles, 20 recent photos (note that we cannot randomly download photos due to the limitations of Instagram API), and their social network (lists of friends and followers). We chose to sample only 50 users here since we are performing manual coding of their photos which is not feasible over large number of users. This dataset allows us to make predictions with a 95% confidence level and a 13% confidence interval for typical users, accurate enough for the analysis in this paper (i.e., the sample is representative).

3.2 Content Categories and Coding Process

To characterize the types of photos posted on Instagram we used a grounded approach to thematize and code (i.e., categorize) a sample of 200 photos from 1,000 photos we obtained (50 users by 20 photo per user). Coming up with good meaningful content categories is known to be challenging, especially for images since they contain much richer features than text. Therefore, as an initial pass, we sought help from computer vision techniques to get an overview of what categories exist in an efficient manner. Specifically, we first used the classical Scale Invariant Feature Transform (SIFT) algorithm (Lowe 1999) to detect and extract local discriminative features from photos in the sample. The feature vectors for photos are of 128 dimensions. Following the standard image vector quantization approach (i.e., SIFT feature clustering (Szeliski 2011)), we obtained the *codebook* vectors for each photo [3]. Finally, we used k-means clustering to obtain 15 clusters of photos where the similarity between two photos are calculated in terms of Euclidean distance between their codebook vectors. These clusters served as an initial set of our coding categories, where each photo belongs to only one category.

[2] It is worth noting that during our crawling process, many users (about 9.4%) changed their privacy settings from public to private which made their profiles and photos unretrievable.

[3] A photo I of a dog can have 125 SIFT features corresponding to the dog's eyes, legs, ears and so on, which are expressed in terms of the codebook vector (of size n) as $I =< C_1 : f_1, C_2 : f_2, C_3 : f_3, ..., C_n : f_n >$, where $\sum_{0 \leq i \leq n} f_i = 125$ and C_i is the cluster of all the features about specific characteristic of an object in the image.

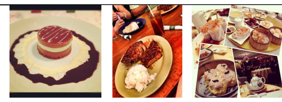
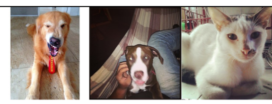
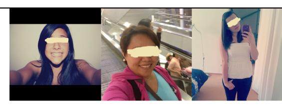
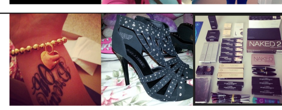
Category	Exemplary Photos
Friends (users posing with others friends; At least two human faces are in the photo)	
Food (food, recipes, cakes, drinks, etc.)	
Gadget (electronic goods, tools, motorbikes, cars, etc.)	
Captioned Photo (pictures with embed text, memes, and so on)	
Pet (animals like cats and dogs which are the main objects in the picture)	
Activity (both outdoor & indoor activities, places where activities happen, e.g., concert, landmarks)	
Selfie (self-portraits; only one human face is present in the photo)	
Fashion (shoes, costumes, makeup, personal belongings, etc.)	

Table 1: 8 Photo Categories

To further improve the quality of this automated categorization, we asked two human coders who are regular users of Instagram to independently examine photos in each one of the 15 categories. They analyzed the affinity of the themes within the category and across categories, and manually adjusted categories if necessary (i.e., move photos to a more appropriate category or merge two categories if their themes are overlapped). Finally, through a discussion session where the two coders exchanged their coding results, discussed their categories and resolved their conflicts, we concluded with 8-category coding scheme of photos (see Table 1) where both coders agreed on, i.e., the Fleiss' kappa is $\kappa = 1$. It is important to note that the stated goal of our coding was to manually provide a descriptive evaluation of photo content, not to hypothesize on the motivation of the user who is posting the photos.

Based on our 8-category coding scheme, the two coders independently categorized the rest of the 800 photos based on their main themes and their descriptions and hashtags if any (e.g., if a photo has a girl with her dog, and the description of this photo is "look at my cute dog", then this photo is categorized into "Pet" category). The coders were asked to assign a single category to each photo (i.e., we avoid dual assignment). The initial Fleiss' kappa is $\kappa = 0.75$. To resolve discrepancies between coders, we asked a third-party judge to view the unresolved photos and assign them to the most appropriate categories.

4 Analysis

This section presents analysis of photo content and user types on Instagram. Our main objective here is to develop a deeper understanding on the types of photos and active users on Instagram. Specifically, we aim to address the following research questions:

- **RQ1:** What kind of photos do people usually post on Instagram?
- **RQ2:** How do the users differ based on the type of images they post?
- **RQ3:** How are these differences between users' photo content related to user's number of followers ?

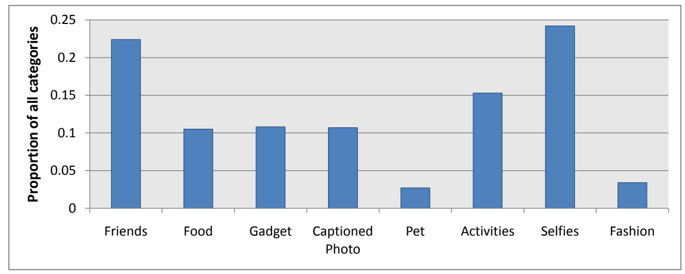


Figure 2: Proportion of Categories

We start with RQ1. Fig. 2 shows the different proportions of photo categories. As shown in this figure, nearly half (46.6%) of the photos in our dataset belong to *Selfies* and *Friends* categories with slightly more self-portraits (24.2% vs. 22.4%). We also notice that *Pet* and *Fashion* are the least popular categories with less than 5% of the total number of images. This corroborates with some of the recent discoveries in popular news media[4]. Other categories – *Food*, *Gadget* and *Captioned photo* contributes to more than 10% individually but are approximately same among themselves. This is in line with the conventional wisdom that Instagram is mostly used for self promoting and social networking with their friends.

We further narrow down this analysis to bolster these findings. Fig. 3 shows the distribution of users in individual categories w.r.t their engagement (which is referred to the number of photos a user posted). For example, 22% users posted 6-8 photos (coded in Friend category) and 26 % users posted 3-5 photos about food (coded in "Food" category). It is interesting to notice that both *Pet* and *Fashion* have a very high standard deviation of 0.5. In contrast, *Selfies* and *Friends* categories show very low standard deviations ($SD = 0.11$ and $SD = 0.124$, respectively). Such a difference indicates that user proportions are more equitably distributed – regardless of their engagement – when it comes to Selfie and Friends photo categories, whereas posting photos about pets and fashion have high variance.

Next, we address RQ2. We perform an analysis to investigate whether there exist different types of users on Instagram based on the content they post. To start with, we first create

[4]http://newsfeed.time.com/2013/12/02/this-collar-camera-lets-your-pet-take-pics-and-post-them-to-instagram/ and http://digiday.com/brands/fashion-brands-instagram/

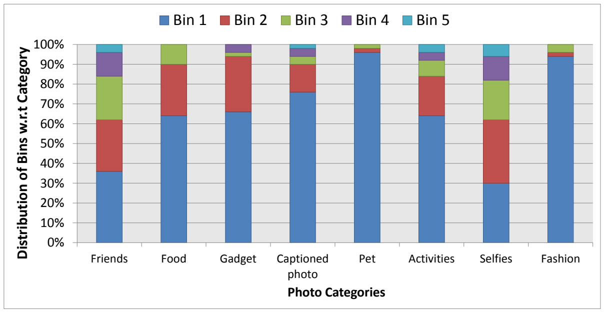


Figure 3: Proportion of users w.r.t content categories. Bin1 contains 0-2 photos; Bin2 contains 3-5 photos; Bin3 contains 6-8 photos; Bin4 contains 9-11 photos; Bin5 contains $\geq$ 11 photos.

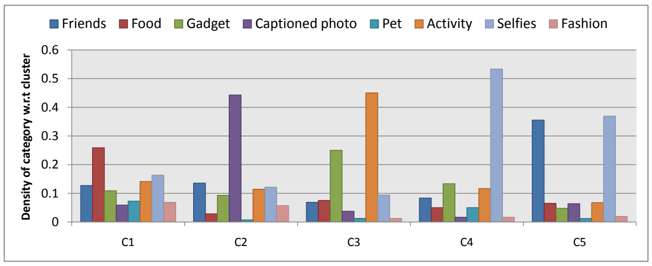


Figure 4: Clustering users based on the categories of their photos. C1 to C5 represent five different user clusters. C1 (n=11, 22%), C2 (n=7, 14%), C3 (n=7, 14%), C4 (n=3, 6%), and C5 (n=22, 44%)

an 8-dimensional vector for each user (since we have 8 categories of photos), where each dimension represents the proportion of user's photos in the corresponding category. After that, we utilize k-means clustering to generate clusters of users accordingly. We perform the clustering multiple times to determine the best k – the number of clusters, whose root mean square error is minimized.

As shown in Fig. 4 shows the clustering results that distinguish 5 types of users. Within each cluster, the histograms indicate the proportion of each of the 8 content categories. The users on Instagam clearly exhibit distinctive characteristics in terms of the photo they share. For example, there exists "selfies-lovers" (C4) who almost post self-portraits exclusively (C4's entropy is *H(x)=1.4*). Similarly, people in C2 post mostly captioned photos whose embedded text mentions about quotes, mottos, poetries or even popular hashtags (C2's entropy *H(x)=1.6*). On the other hand, there exist common users like C1 where even though they focus (slightly) more on posting photos of food, they like to post other categories of photos as well. Therefore, C1's entropy is the highest (*H(x)=1.96*). Also, it is interesting to know that people in C5 (22 users in total) care about their friends as seriously as caring about themselves, by posting nearly equal number of photos from both categories (while ignoring the other categories) (C5's entropy is *H(x)=1.54*).

To answer RQ3, we examine if the type of users directly correlates with the users' number of followers. In other words, do "selfies-lovers" (C4) attract significantly more followers than common users in C1? To this end, we perform a two-tailed t-test on the follower distributions from different user clusters. We find that all the other types of users agree with the null hypothesis that followers are independent of the user clusters (two-tailed t-test; p–value = 0.171). Since our analysis does not show any statistical significance over the "number of followers – types of users" correlations, we conclude that the size of a user's audience (followers) is independent of the type of the user (characterized in terms of the user's shared photos on Instagram).

5 Conclusions and Future Work

In this paper, we performed an analysis of photos and users on Instagram – the fastest growing social media application. To our knowledge, this is the first paper that conducts such analysis on Instagram data. In this paper we have shown how the image data was handled and analyzed to answer three fundamental research questions on Instagram. Our analysis shows that there are largely 8 different types of photo categories on Instagram. Based on the content posted by users, this analysis derives 5 different types of users (or user clusters). We also showed that there is no direct relationship between the number of followers and the type of users characterized in terms of her shared photos, through statistical significance tests. As a part of our future work, we want to extend this work by incorporating other features on Instagram such as user's bio, hashtags, comments, and social network. We also plan to analyze sentiments and events associated with the photos and their associated text (Hu, Wang, and Kambhampati 2013).

Acknowledgements This research is supported in part by the ONR grants N00014-13-1-0176, N0014-13-1-0519, ARO grant W911NF-13-1-0023 and a Google Research Grant.

References

Ellison, N. B., et al. 2007. Social network sites: Definition, history, and scholarship. *JCMC*.

Hochman, N., and Manovich, L. 2013. Zooming into an instagram city: Reading the local through social media. *First Monday*.

Hu, Y.; Wang, F.; and Kambhampati, S. 2013. Listening to the crowd: automated analysis of events via aggregated twitter sentiment. In *IJCAI*.

Instagram. 2013. Instagram statistics. {`http://instagram.com/press/`}.

Lowe, D. G. 1999. Object recognition from local scale-invariant features. In *CVPR*.

McCune, Z. 2011. Consumer production in social media networks : A case study of the instagram iphone app. *Dissertation, University of Cambridge*.

Naaman, M.; Boase, J.; and Lai, C.-H. 2010. Is it really about me?: message content in social awareness streams. In *CSCW*.

Rainie, L.; Brenner, J.; and Purcell, K. 2012. Photos and videos as social currency online. *Pew Internet & American Life Project*.

Silva, T. H.; Melo, P. O.; Almeida, J. M.; Salles, J.; and Loureiro, A. A. 2013. A picture of instagram is worth more than a thousand words: Workload characterization and application. In *DCOSS*. IEEE.

Szeliski, R. 2011. *Computer vision: algorithms and applications*. Springer.