Filtered Food and Nofilter Landscapes: Role of Content and Visual Effects in Photo Engagement

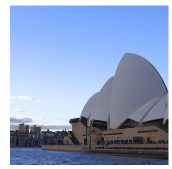
Abstract

Millions of images are shared through social media every day. Yet, we know little about how the activities and preferences of users are dependent on the content of these images. In this paper, we seek to understand viewers engagement with photos. We design a quantitative study to expand previous research on in-app visual effects (also known as filters) through the examination of visual content identified through computer vision. This study is based on analysis of 4.9M Flickr images and is organized around three important engagement factors, likes, comments and favorites. We find that filtered photos are not equally engaging across different categories of content. Photos of food and people attract more engagement when filters are used, while photos of natural scenes and photos taken at night are more engaging when left unfiltered. In addition to contributing to the research around social media engagement and photography practices, our findings offer several design implications for mobile photo sharing platforms.

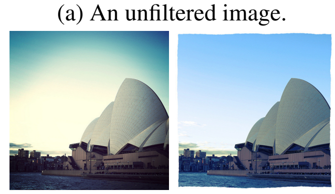
Introduction

The type of media shared through social media channels has shifted from text content to include an increasingly large number of images. The traces of the stories, images, and videos that we view online can reveal insights about our habits, activities and preferences. The role of social network-related factors on our preferences have been well studied in previous research. Yet, few studies have sought to understand how user behavior and interaction with content is dependent on the image itself.

Past research has developed qualitative techniques to understand the ways in which images reflect social and cultural norms (Kress and Van Leeuwen 1996; Mitchell 2011; Rose 2012). On the other hand, computer vision has made it possible to automate the process of classifying the content of these visual artifacts (Bhatt and Kankanhalli 2011; Branson et al. 2010; Vedaldi and Fulkerson 2010). These approaches each provide distinct benefits for working with images, however they are rarely integrated. The research that investigates the image properties is often detached from the social meanings of the photograph and the research that focuses on the social behavior often ignores what is in the image. This work bridges this gap by connecting social and visual research through studies of photo engagement.



(a) An unfiltered image.



(b) Mammoth and Chameleon Filters

(c) Chinchilla and Orca filters.

Figure 1: Examples of (a) an unfiltered photo, (b) some popular filters, and (c) some unpopular filters from a sample of Flickr photos.

Images are viewed as having the ability to perform multiple *semiotic*, or meaning-making roles (Kress and Van Leeuwen 1996). These roles are based on the idea and the social meaning of the photo. They include (i) representing ideas; (ii) mediating interactions between makers and viewers; (iii) providing genre specific cues for meaning-making activities.

We assert these simple, human-perceivable cues from the image can be used to understand the social meanings carried out by the photograph. To do this, one must extract several features from images uploaded to Flickr and use them to model photo engagement; controlling for the well-known factors influencing engagement such as network structure and user activity. Our work is focused on two dimensions of information in the image: the presentation and the content.

Building on recent work (Bakhshi et al. 2015) that found filtered photos more engaging than non-filtered ones, we aim to explore this engagement across different classes of images. By testing various categories of image content, we find that not all classes of images show similar engagement with filters. For example photos of natural scenes are more engaging when not filtered and photos of food are more engaging when filtered. In this work, our contributions are (i) to social computing research by emphasizing the importance of visual effects and content of images in impacting user behavior, and (ii) to interaction design by emphasizing the agency of these behaviors in shaping and maintaining interactions.

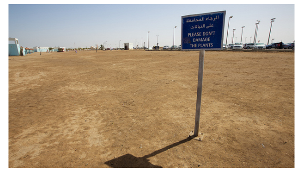
Related Work

Van House et al. (2004) predicted that the camera phones would become the most predominant consumer imaging device. Today, the increased access to mobile camera phones and large amount of storage makes it easier to access photographs and so the visual interaction became more common. This trend has been going on for a while with some scholarly work in the area of photographic communication through mobile devices. Kindberg (2005), for example, introduced the mobile photographic communication as a new genre in communication.

Most of the existing research on camera phones focuses on the sending of images and the various ways in which people use their devices (Ling, Julsrud, and Yttri 2005; Makela et al. 2000). Most of which are carried in the context of communication via MMS (Frehner 2008; Ling and Julsrud 2004; Scifo 2005). and the main method of research in these studies are based on qualitative findings through interviews (Kindberg et al. 2004; 2005; Koskinen 2005; Kurvinen 2003). These studies are usually based on a small sample of users and do not always generalize to the larger population of camera phone users but do provide early insights into photography, mobile, and sharing (Koskinen et al. 2002; Sarvas et al. 2004; Davis et al. 2005; Van House et al. 2005).

In the social media space, previous literature shed light on those aspects of images that can help with social connections. Lin and Faste (2012) highlight the potential of images to promote social connections in the online space. Contextual interviews focusing on users' photo sharing, organizing, and viewing behaviors indicated that people are socially motivated by photographs, are selective in what they view, and use photographic narratives to correspond with others and to browse information. McDonald (2007) in a paper looking across several online communities, identified four types of visual conversation styles evident through posted images: positional play, image quote, text-in-picture, and animation.

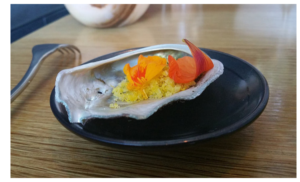
The visual content of photos themselves are not widely understood. In a recent research performed on Instagram data (Bakhshi, Shamma, and Gilbert 2014) studied the engagement value of photos that had faces in them. They found that photos with faces are more likely to receive engagement through likes and comments. Later these photos were shown to have diversity if those individuals in the photos were smiling (Singh, Atrey, and Hegde 2017). Further research looks at groupings of visual features and analyzes their popularity (Hu, Manikonda, and Kambhampati 2014). The most relevant work to ours is the work that looks at the effect of visual artifacts (filters) on photo engagement (Bakhshi et al. 2015). In our work we extend this past research by using modern computer vision artificial intelligence to determine what is in the photo itself and provide an understanding of photo engagement with filters and that content.



(a) Visual tag: *Outdoor*.

(b) Visual tag: *Text*.

(c) Visual tag: *Low-light*.



(d) Visual tag: *Food*.

Figure 2: Examples of photos of with some (computer vision) auto-tags.

In HCI research, there is a great deal of work exploring the benefits of using face icons and faces in interfaces (Laurel 1997; Sproull et al. 1996; Takeuchi and Nagao 1993). Walker et al. (1994) studied how having faces and facial expressions for a computer application affects users' performance and productivity. They compared subjects' responses to an interview survey under three conditions: questions spoken by a synthesized face with neutral expressions, spoken by a face with stern expressions, or text only. Subjects who responded to the spoken face made more effort to answer the questions by spending more time, writing more comments and making fewer mistakes. They reported that having a face is engaging and takes more effort and attention from the user.

Previous research (Takeuchi and Naito 1995) compared users' impressions of an agent which helped them to win a card game. They showed that users respond differently to systems having a face than to those without. Studies on embodied interfaces showed similar results. Agents are visual digital representations of a computer interface often in the form of human-like faces (Cassell 2000). In a review study of embodied agents (Dehn and Van Mulken 2000), authors reported that adding an embodied agent to an interface made the experience more engaging.

Methods

We take a quantitative approach and analyze data collected from Flickr mobile app in order to understand the role of filters in engaging users across various types of content

Flickr Mobile Data

In this paper, we aim to understand the impact of filters and content of photos on social engagement as measured in photo *views*, *comments*, and *favorites*. We are particularly interested in the differences in filtered engagement based on the content of the photo. In this section, we describe our data collection process and summarize the descriptive statistics of our meta data.

We collected public photo meta-data from Flickr in November 2015. These photos were identified by Flickr as having been uploaded from Flickr's mobile app. In total, the dataset consists of over 4.9 million photos. We identified whether the photos were posted as original or filtered by checking their machine tags, auto-generated tags from the uploading application. 3.5 million of the photos are uploaded using the iOS app and 1.4 million are uploaded using Android app. We also identified the type of the filter that was applied; Figure 1 shows a sample set of filters on Flickr mobile app.

Flickr's AI tagging (called Auto-tags) detects certain objects (e.g. food and flower), certain landscapes (e.g. beach and mountain) and faces of people (including people, portrait and groupshot). The visual analysis also determines whether the photo is taken in low-light, has text or is taken outdoors. With every visual tag detected in the image, Flickr reports a confidence level. For example, if the visual analysis has detected a face with 99% confidence, the visual tag shows the level of the confidence along with the visual tag of the face. In this study we only use visual tags with level of confidence higher than 95%. Figure 2 shows some Auto-tag examples.

Dependent Features.

Finally, we extracted several statistics that will be used as our dependent features[1]. These are the number of views, comments, and favorites that each photo had acquired since its posting. These were obtained via the Flickr API for analysis. Our three models of photo engagement are based on implicit and explicit signals (Yew and Shamma 2011).

Views We use number of *views* of each photo as an implicit measure of engagement or consumption of content. It quantifies the number of distinct users who viewed the photo. The higher number of *views* suggests that the photo was consumed by more number of people.

Comments *Comments* are explicit forms of actions taken on each photo. The higher number of *comments* shows that the photo received more explicit attention.

Favorites Favorites on a photo quantify the amount of explicit interest in the photo. The number of favorites is the number of distinct users who favorited the photo. On Flickr, favorites are used both for bookmark a photo and also as a social signal similar to *like* on Instagram or Facebook.

Flickr also has an Explore page which features the most popular photos on site over the past day. While the actual ranking function is kept secret, it is known to be some function of these dependent features at its core (Butterfield et al. 2014). As they are directly related, Explored photos were not specifically accounted for.

[1]This dataset will be made available with the publication

Control Features.

There are four control features that might affect the engagement of a photo.

Photostream views When a user uploads a public photo, it is pushed to all of that user's followers such that when a follower opens the mobile application or the website, that pushed photo appears in the stream of all photos from people they follow. For the purpose of this study we only consider photos that are public and visible to everyone. *Photostream* quantifies the level of implicit action (the photo was viewed but not clicked) mainly as a function of the user's popularity. *Photostream* views are usually obtained by directly viewing the user's profile.

Followers Like Twitter, the Flickr's relationship model between people is asymmetric: users form into social networks based on *follow* relationships. The number of followers is our measure of the user's audience size. This is a powerful and intuitive control, as we would expect users with more *followers* to have higher baseline probability of being *viewed*, *commented* or *favorited* by their followers.

Tags Tags on Flickr are used by the search index to help people find photos. The higher number of tags usually imply that the photo will appear in more relevant searches and as a result may have higher chances of being viewed. We use the number of *tags* to control for higher likelihood of appearing in search results.

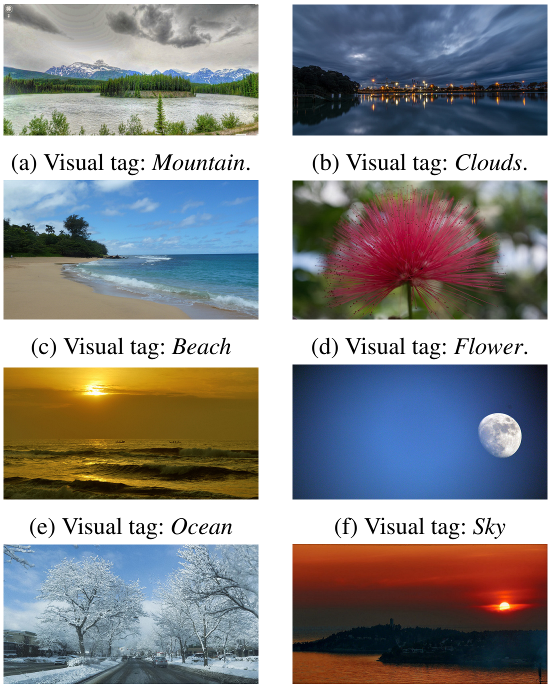
Photos We use the number of *photos* as a control for level of activity. Users who post more photos on Flickr are considered active creators of content. The higher number of *photos* posted on one's profile usually contributes to lower likelihood of a single photo being viewed.

Filter and Content Features

Our focus in this study is to determine the impact of visual effects on each type of photo content, and understand how they drive or hinder engagement. We describe our features of interest in the following.

Filter feature For every image, we identify whether it was shared as original or it was *filtered* before shared. We do so by checking the photos automatically generated tags that are created by the uploading app. We code a new variable *is filtered* as a binary variable, with a value of 1 for filtered photos and 0 otherwise.

Content type Flickr automatically identifies several types of objects or landscapes in the photos. It uses advanced vision algorithms and reports detected scenes or objects with a confidence percentage using an automatic tag. We group these tags into natural scenes (beach, clouds, flower, mountain, ocean, sky, snow or sunset), people (face, portrait, groupshot), outdoor, text, low-light and food. We use a categorical variable that codes each photo with any of these categories of photos. Figure 3 shows examples of content types that are categorized into natural scenes.



(a) Visual tag: *Mountain*. (b) Visual tag: *Clouds*.

(c) Visual tag: *Beach* (d) Visual tag: *Flower*.

(e) Visual tag: *Ocean* (f) Visual tag: *Sky*

(g) Visual tag: *Snow* (h) Visual tag: *Sunset*.

Figure 3: Examples of photos of natural scene uploaded on Flickr. Each photo was tagged via AI (or Autotagged) by one or more tags related to natural scenes.

Modeling engagement

The number of *views*, *comments* and *favorites* are all count variables. We model them using *Negative Binomial* regression on two classes of independent variables: control features and features of interest (filters and content). Negative Binomial regression is well-suited for *over-dispersed* distributions of count dependent variable (Cameron and Trivedi 1998). We use Negative Binomial regression instead of Poisson regression since the variance of the dependent variables are larger than their means ($\mu_{\text{views}} = 49.87$, $\sigma_{\text{views}} = 351.74$, $\mu_{\text{comments}} = 0.11$, $\sigma_{\text{comments}} = 1.40$, $\mu_{\text{favorites}} = 0.36$, $\sigma_{\text{favorites}} = 3.76$). We use *over-dispersion* to test whether Poisson or Negative Binomial regression should be used. This test was suggested by Cameron and Trivedi (Cameron and Trivedi 1998), and involves a simple least-squares regression to test the statistical significance of the over-dispersion coefficient.

The Negative Binomial regression models the *expected* number of *views* (y_{views}), *comments* (y_{comments}), or *favorites* ($y_{\text{favorites}}$), for a photo as a function of control, filter and content features. For each dependent measure, we construct two regression models to evaluate the *impact* of control and interest variables: first to model the control variables alone (control model), and second to model both control variables as well as filter and content variables (full model). The reduction in deviance from the full model to the control-only model shows the significance of our features (filters and content) on describing the number of *views*, *comments* and *favorites*.

The first model uses control attributes as predictors of the number of *views*, *comments* or *favorites* on a photo. Since all the models use the same predictors and they only differ in the dependent measure, we use y to refer to dependent features (*views*, *comments* and *favorites*).

$$\ln(y) = I + \Sigma_i^{x_i \in \text{controls}} \beta_i x_i \tag{1}$$

where I is the intercept for the model and the control sum is computed using the following control attributes:

$$\begin{aligned}\Sigma_i^{x_i \in \text{controls}} \beta_i x_i &= \beta_{\text{photostream}} x_{\text{photostream}} + \beta_{\text{tags}} x_{\text{tags}} \\ &+ \beta_{\text{followers}} x_{\text{followers}} + \beta_{\text{no\_photos}} x_{\text{no\_photos}}\end{aligned} \tag{2}$$

This model allows us to understand the effect on the number of *views*, *comments* and *favorites* of control variables alone. We then model the impact of filters and content types on the number of *views*, *comments* and *favorites*. We construct a second model that includes control features, filter variable and content features:

$$\begin{aligned}\Sigma_j^{x_j \in \text{interest}} \beta_j x_j &= I + \Sigma_i^{x_i \in \text{controls}} \beta_i x_i \\ &+ \beta_{\text{is\_filtered}} x_{\text{is\_filtered}} + \beta_{\text{content}} x_{\text{content}} \\ &+ \beta_{\text{is\_filtered+content}} x_{\text{is\_filtered}} x_{\text{content}}\end{aligned} \tag{3}$$

Where, the controls sum is taken from equation 2. The regression coefficients β allow us to understand the effect of an independent variable on the number of *views*, *comments* and *favorites* (note that to be able to compare coefficients, we z-score all numerical variables before performing regression).

We test coefficients of all independent variables for the null hypothesis of a zero-valued coefficient (two-sided). This method is based on standard errors of coefficients, which is analogous to the *t-test* used in conventional regression analyses. We use a Chi-square test with one degree of freedom to test the hypothesis that each coefficient β_j is zero. To do this, we compute the following term:

$$\chi^2 = \frac{b_j^2}{(SE_j)^2} \tag{4}$$

where, b_j is the estimate of β_j and SE_j is the standard error of the coefficient β_j. Table 2 shows the β coefficients and the p-values from the Chi-square test. We see that all independent variables have coefficients that are statistically significant.

We use the deviance goodness of fit test to assess our regression fit (Hilbe 2011). The deviance is expressed as:

$$D = 2\sum_{i=1}^{n}(\zeta(y_i; y_i) - \zeta(\mu_i; y_i)) \tag{5}$$

with $\zeta(y_i; y_i)$ indicating a log-likelihood function with every value of μ given the value y in its place. The $\zeta(\mu_i; y_i)$ is the log-likelihood function for the model being estimated.

The deviance is a comparative statistic. We use the Chi-square test to find the significance of the regression model, with the value of deviance and the degrees of freedom as two Chi-square parameters. The degrees of freedom is the number of predictors in each model. Tables 1a, 1b and 1c summarize the model parameters and the goodness of fit test results, showing that the regression models are a good fit for our data.

Model	θ	Resid. df	$2 \times$ log-lik.
control model	0.43	2946943	-29195091.96
full model	0.44	3030060	-29158614.06
Summary			
LR.stat		22993	
degrees of freedom		18	
$\Pr(> \chi^2)$		$< 10^{-15}$	

(a) Views model.

Model	θ	Resid. df	$2 \times$ log-lik.
control model	0.07	414999	-1575770.07
full model	0.07	477135	-1569749.08
Summary			
LR.stat		62136	
degrees of freedom		18	
$\Pr(> \chi^2)$		$< 10^{-15}$	

(b) Comments model.

Model	θ	Resid. df	$2 \times$ log-lik.
control model	0.18	1269819	-3259137.89
full model	0.18	1376276	-3255783.73
Summary			
LR.stat		106457	
degrees of freedom		18	
$\Pr(> \chi^2)$		$< 10^{-15}$	

(c) Favorites model.

Table 1: Summary of the models from equation 2 and 3 for the number of (1a) views, (1b) comments, and (1c) favorites. θ is the shape parameter of negative binomial distribution, Resid. df is the residuals degree of freedom for the fitted model. The chi-square test rejects the hypothesis and so the full model is significant.

	control model		full model	
Variable	β	Std.Err	β	Std.Err
(Intercept)	3.17	0.00	3.14	0.00
tags	0.14	0.00	0.16	0.00
photostream views	0.89	0.00	0.88	0.00
photos	-0.84	0.00	-0.83	0.00
followers	0.93	0.00	0.93	0.00
is filtered			0.19	0.03
content:food			0.29	0.01
content:nature			0.37	0.00
content:low-light			-0.28	0.01
content:outdoor			0.11	0.00
content:people			0.23	0.00
content:text			-0.27	0.01
is filtered & content:food			0.15	0.04
is filtered & content:nature			-0.17	0.03
is filtered & content:low-light			-0.23	0.04
is filtered & content:outdoor			-0.21	0.03
is filtered & content:people			0.24	0.03
is filtered & content:text			-0.17	0.03

Table 2: **View Model.** Results of negative binomial regression with number of views as dependent variables. p values are $< 2 \times 10^{-4}$ for all variables.

Results

In this section, we discuss results of our work.

Effect of Control Variables

The first class of variables we study are our control variables. In particular we look at the effect of *photostream views*, *number of photos* posted by user, *number of tags* on the photo and *number of followers* of the user. Tables 2, 3 and 4 summarize the β coefficients for both control and full models with *views*, *comments* and *favorites* as dependent variables. The models significance are summarized in Tables 1a, 1b and 1c. All control models for views, comments and favorites show significance, $p < 10^{-15}$, for all predictors.

We use the Chi-square Test to find the significance of the regression model, by computing the reduction in deviance from a *null model*. Tables 1a, 1b and 1c summarize the significance of each model. Now, we discuss the effect of each of these control variables.

Effect of Photostream views We use *Photostream views* as a control measure for the amount of engagement a photo receives due to user profile views. As expected, *photostream views* is a strong predictor for the number of *views*, *comments* and *favorites* on Flickr. The relationship between *photostream views* and *views* is strong ($\beta = 0.89$, $p < 2 \times 10^{-16}$) and expected. The higher volume of visits to one's profile leads to the higher likelihood of each photo receiving *views*. We find that the size of β coefficient compared to other control variables such as *followers* is much larger in views model compared to comments and favorites model. In the comments model *photostream's* effect is significant ($\beta = 0.46$, $p < 2 \times 10^{-16}$) but smaller than 1/3 of the *followers* effect. We see similar

	control model		full model	
Variable	β	Std.Err	β	Std.Err
(Intercept)	-3.27	0.00	-3.16	0.02
tags	0.17	0.00	0.19	0.00
photostream views	0.46	0.01	0.46	0.01
photos	-1.21	0.01	-1.21	0.01
followers	1.59	0.00	1.59	0.00
is filtered			0.37	0.09
content:food			0.28	0.03
content:nature			0.16	0.02
content:low-light			-0.06	0.03
content:outdoor			0.15	0.02
content:people			0.20	0.02
content:text			-0.18	0.02
is filtered & content:food			0.11	0.03
is filtered & content:nature			-0.31	0.09
is filtered & content:low-light			-0.40	0.12
is filtered & content:outdoor			-0.32	0.10
is filtered & content:people			0.37	0.10
is filtered & content:text			-0.40	0.10

Table 3: **Comments Model.** Results of negative binomial regression with number of comments as dependent variables. For all variables p values is $< 2 \times 10^{-4}$.

	control model		full model	
Variable	β	Std.Err	β	Std.Err
(Intercept)	-2.33	0.00	-2.30	0.01
tags	0.22	0.00	0.22	0.00
photostream views	0.65	0.00	0.65	0.00
photos	-1.47	0.00	-1.48	0.00
followers	1.68	0.00	1.67	0.00
is filtered			0.64	0.06
content:food			0.15	0.02
content:nature			0.08	0.01
content:low-light			-0.01	0.02
content:outdoor			0.10	0.12
content:people			0.04	0.01
content:text			-0.01	0.01
is filtered & content:food			0.62	0.09
is filtered & content:nature			-0.20	0.06
is filtered & content:low-light			-0.30	0.08
is filtered & content:outdoor			-0.30	0.06
is filtered & content:people			0.52	0.06
is filtered & content:text			-0.27	0.06

Table 4: **Favorites Model.** Results of negative binomial regression with number of favorites as dependent variables. Except for content:low-light (where $p < 2^{-2}$ all other p values are $< 2 \times 10^{-4}$.)

pattern in the favorites model ($\beta = 0.65, < 2 \times 10^{-16}$). This suggests that while *photostream views* is a strong predictor for the number of *views*, its role in predicting the number of *comments* or *favorites* is significantly lower than the effect of *followers*.

Effect of Followers We use *followers* as a feature to control for user's influence. The size of user's audience leads to higher likelihood of receiving *views*, and as a result may impact *comments* and *favorites*. From the views model, summarized in Table 2, we see that the *followers* feature is a largest contributor to the number of *views* ($\beta = 0.93$, $p < 2 \times 10^{-16}$), to the number of *comments* ($\beta = 1.59$, $p < 2 \times 10^{-16}$) and to the number of *favorites* ($\beta = 1.68$, $p < 2 \times 10^{-16}$)

Effect of Tags *Tags* on Flickr have an important role in photo discovery by search. We use the number of *tags* to control for likelihood of finding photos through search. Our engagement models of *views*, *comments* and *favorites* show that the role of *phtags in predicting* views*, com*ments *and* favorites *is not as strong as other control features such as* photostream views *or* followers*. While tags are positively related to the number of* views *($\beta = 0.14$, $p < 2 \times 10^{-16}$), this relationship is not strong. The same trend holds in the* comments *model ($\beta = 0.17$, $p < 2 \times 10^{-16}$) and* favorites *model ($\beta = 0.22$, $p < 2 \times 10^{-16}$).*

Effect of Photos *We control for the user's level of activity by considering the number of* photos *as an independent variable. The effect of activity on all dependent variables is negative, in all models of* views *($\beta = -0.84$, $p < 2 \times 10^{-16}$),* comments *($\beta = -1.21$, $p < 2 \times 10^{-16}$) and* favorites *($\beta = -1.47$, $p < 2 \times 10^{-16}$), it is a significant and large effect. Intuitively, the likelihood of per photo engagement decreases with the increase in the number of* photos.

Effect of Filters and Content

The main objective in this paper is to evaluate the impact and interplay of filters and photo content with regards to social platform engagement. First we briefly discuss the general role of visual filters. Next we discuss the effect of content. This is illustrated through various visual categories: food, nature, low-light, outdoor, people, and text; the effect of filters and people is congruent with previous research in the field (Bakhshi, Shamma, and Gilbert 2014; Bakhshi et al. 2015)

Effect of Filters.

We first summarize the effects of filters on different engagement metrics. With regards to *views*, our results show that filters are strongly positively correlated with the number of *views* ($\beta = 0.19$, $p < 2 \times 10^{-16}$). For the categorical variables such as filters we can calculate the *Incidence Risk Ratio* to quantify the effect with respect to reference category. For the *views* we have: $IRR = 21\%$ which means that filtered photos are 21% more likely to be viewed compared to non-filtered photos.

The relationship between filtered photos and *comments* is strong and positive as well ($\beta = 0.37$, $p < 2 \times 10^{-16}$) $IRR = 45\%$. It is 1.41 times more likely for a filtered photo to receive comments compared to an original photo. In the case of *favorites*, the relationship is strong as well ($\beta = 0.64$, $p < 2 \times 10^{-16}$, $IRR = 90\%$), suggesting that it is 90% more likely for filtered photos to receive favorites compared non-filtered photos.

Effect of Content.

We use a categorical variable to quantify effect of different content types on photo engagement. Our results in Tables 2, 3 and 4 summarize the effect of photo content on engagement. We find that some groups of the photo content, such as food, outdoor and people, are more likely to be engaging than others. We also analyze the impact of filtered photos across each group of content and find that some photo categories are more popular when filtered. For example filtered photos of food and people are significantly more likely to be engaging than non-filtered photos. We describe the results of each photo content in the following.

Content: Food Photos of food are highly likely to be viewed by Flickr users ($\beta = 0.29$, $p < 2 \times 10^{-16}$, $IRR = 34\%$). They are highly likely to be commented on ($\beta = 0.28$, $p < 2 \times 10^{-16}$, $IRR = 32\%$) and favorited ($\beta = 0.15$, $p < 2 \times 10^{-16}$, $IRR = 16\%$) as well. This suggests that photos of food are more popular than other types of content on Flickr and they are 34% more likely to be viewed, 32% more likely to be commented on and 16% more likely to be favorited.

On the other hand, photos of food that are filtered are more likely to be viewed ($\beta = 0.15$, $p < 7 \times 10^{-4}$, $IRR = 16\%$) compared to the ones that are posted without any filters. We don't see significant effects of filtered photos of food on comments and favorites, therefore, we cannot make claims on those types of engagements. It is, however, interesting that filtered photos of food are 16% more likely to be viewed by Flickr users.

Content: Nature Photos of nature are highly likely to be viewed ($\beta = 0.37$, $p < 6 \times 10^{-15}$, $IRR = 45\%$) on Flickr. Nature photos are also likely to be commented on ($\beta = 0.16$, $p < 2 \times 10^{-16}$, $IRR = 17\%$) but not as much likely to receive more favorites ($\beta = 0.08$, $p < 2 \times 10^{-16}$, $IRR = 8\%$) compared to other photo contents.

On the contrary, we see that filtered photos of nature are less likely to be viewed ($\beta = -0.17$, $p < 2 \times 10^{-4}$, $IRR = 18\%$), less likely to be commented on ($\beta = -0.31$, $p < \times 10^{-3}$, $IRR = 36\%$) and less likely to be favorited ($\beta = -0.20$, $p < \times 10^{-3}$, $IRR = 22\%$). This finding suggests that filtered photos of nature (sky, clouds, mountains, beaches, etc.) are 18% less likely to be viewed, 36% less likely to be commented on and 22% less likely to be favorited, implying that photos of nature are more popular when posted as original.

Content: Low-light Photos taken in low-light are less likely to be viewed by Flickr users ($\beta = -0.28$, $p < 2 \times 10^{-16}$, $IRR = 32\%$) but their relationships with comments ($\beta = -0.06$, $p = 0.02$) and favorites ($\beta = -0.01$, $p = 0.03$) are not significant. This could be due to low quality of photos taken by mobile cameras in low-light settings. We also see that filtered photos taken in low-light are less likely to be viewed ($\beta = -0.23$, $p < 2 \times 10^{-10}$, $IRR = 26\%$), less likely to be commented on ($\beta = -0.40$, $p < 9 \times 10^{-4}$, $IRR = 49\%$) and less likely to be favorited ($\beta = -0.30$, $p < 2 \times 10^{-4}$, $IRR = 35\%$). This suggests that filters are contradictory to engagement for photos taken in low-light. In terms of filtering the low-light photos, we have to take into account the original photos are not great at the first place. There are not many options to modify a photo that is dark and does not have many colors.

Content: Outdoor The outdoor photos on Flickr are more likely to be viewed ($\beta = 0.11$, $p < 2 \times 10^{-16}$, $IRR = 12\%$), more likely to be commented on ($\beta = 0.15$, $p < 1 \times 10^{-13}$, $IRR = 16\%$) and more likely to be favorited ($\beta = 0.10$, $p < 4 \times 10^{-16}$, $IRR = 10\%$). On the other hand filtered photos of outdoor are less likely to be viewed ($\beta = -0.21$, $p < 5 \times 10^{-11}$, $IRR = 23\%$), less likely to be commented on ($\beta = -0.32$, $p < 8 \times 10^{-4}$, $IRR = 38\%$) and less likely to be favorited ($\beta = -0.30$, $p < 5 \times 10^{-6}$, $IRR = 35\%$). That could be why photos of outdoors are engaging on Flickr. Although, we did not find a significant correlation between photos of nature and photos of outdoor, most photos of natural scenes are taken outdoors.

Content: People Photos of people are more likely to be viewed ($\beta = 0.24$, $p < 4 \times 10^{-14}$, $IRR = 27\%$), more likely to be commented on ($\beta = 0.20$, $p < 2 \times 10^{-16}$, $IRR = 22\%$). The effect of photos of people on favorites is positive but small ($\beta = 0.04$, $p < 4 \times 10^{-5}$, $IRR = 4\%$). When photos of people are filtered they are significantly more likely to be viewed ($\beta = 0.24$, $p < 4 \times 10^{-14}$, $IRR = 27\%$), more likely to be commented on ($\beta = 0.37$, $p < 2 \times 10^{-5}$, $IRR = 45\%$) and more likely to be favorited ($\beta = 0.52$, $p < 2 \times 10^{-15}$, $IRR = 68\%$). This suggests that photos of people are generally more likely to be engaging for Flickr users but also if they are filtered they are significantly more engaging than when they are posted as original.

Content:Text Photos that contain text are less likely to be viewed ($\beta = -0.27$, $p < 2 \times 10^{-16}$, $IRR = 31\%$), less likely to be commented on ($\beta = -0.18$, $p < 2 \times 10^{-16}$, $IRR = 20\%$). The p-value for effect of text content on favorites is large ($p = 0.41$) and so we cannot claim anything on this effect. When photos of text content are filtered they are less likely to be viewed ($\beta = -0.17$, $p < 6 \times 10^{-8}$, $IRR = 19\%$), less likely to be commented on ($\beta = -0.40$, $p < 6 \times 10^{-5}$, $IRR = 49\%$) and less likely to be favorited ($\beta = -0.27$, $p < 3 \times 10^{-5}$, $IRR = 31\%$). The findings imply that photos that contain text are generally less engaging specially if they are filtered.

Discussion

Filters are becoming increasingly popular among users of mobile photo sharing tools and sites. Currently they are provided on mobile apps as generic tools for post-processing of photos. Previous work has shown that filters improve engagement of the photos. In this work, we show while in general filters are engaging, their effect on different types of content varies significantly, with negative impact on some categories of content. Using advanced vision techniques provided by Flickr vision algorithms, we detect several groups of photo content, including people, nature, outdoor, food, text and low-light and evaluate their role in engaging users, both when they are filtered and when they are not filtered.

In studying the role of filters and content in photo engagement, we do our best to find a middle ground between interaction design research, and visual engagement studies. Many of the control variables, like the number of followers, have a clear effect on engagement; recent research has show similar engagement lifts in the general use of filters (Bakhshi et al. 2015). However, here we find the photograph content can counter this general filter engagement lift (as we find in nature photos) or even further boost the engagement (as we see in food photos). This carries implications into predictive work to auto-filter images (Sun et al. 2017). By adopting an analytical approach, we hope to contribute in both ways: to interaction design by emphasizing the importance of visual content on interaction and, second, to visual engagement studies by emphasizing the agency of visual effects on various types of content in shaping engagement.

Social Network Size is the Main Contributor to Photo Engagement

With analysis of our control variables (photostream views, followers, photos and tags) we find that the size of social network audience is the main contributor to engagement values of a photo. Recent studies on Instagram (Bakhshi, Shamma, and Gilbert 2014) and Flickr (Bakhshi et al. 2015) found similar patterns across photos posted on Instagram. On the other hand, some of the work conducted on other social networks such as Twitter (Cha et al. 2010) found that the number of followers is not the only factor shaping the influence of a user and the type of topics and content of posts are also important factors in determining popularity levels of the post. Here, we find strong evidence that the social network reach, the number of followers, is a significant predictor of the engagement factors around the image but not the only one. For example we see that photostream views is also strongly related to the number of views, however the level of engagement predicted by the photostream views on comments and favorites is not as strong. This suggests that while social network reach is the main factor contributing to all types of engagement, it is relatively more impactful on comments and favorites compared to the photostream views. One scenario that can explain such observation is photo discovery through social network followers, compared with the photo discovery through Flickr profiles. While both seem to be highly impacting the views, the number of comments and favorites are more influenced by the social network.

We also find that tags are not as significant contributors to engagement as photostream views or followers. Tags are usually used as another way to discover a photo on Flickr. Users search for a specific content by a tag name and the photos associated with that tag appear in the search results. From the comparison between effect sizes of tags, photostream views and followers we can hypothesize that tags are not as effective in discovery of a photo and engaging the user with the photo as the other two methods are.

Finally, the number of photos are negatively related to the engagement level they receive. This suggests that the likelihood of a photo being noticed among pool of photos decreases with higher number of photos on the profile. The more number of photos shared by the user, the less likely each photo is to receive views, comments and favorites.

Filters Boost Engagement

Similar to previous work (Bakhshi et al. 2015), we find that in general, filtered photos are more engaging than original photos. Filtered photos are 62% more likely to be viewed, 141% more likely to be discussed in comments, and 90% more likely to be added as favorites. We find that this effect highly depends on the content of photo. Our results are significant, even with presence of several control factors such as *photostream views*, *tags*, *followers* and user's *activity* level.

The finding that filtered photos are significantly more engaging than non-filtered photos suggest that the mobile photographers like adding features and effects to their photos and their viewers prefer them to the original photos. Given that mobile photographers are not necessarily professional photographers, adding features such as filters makes the photo appear more professional or cool.

It is worth mentioning that while filters may help the presentation of photos, the ability to edit photographs has not turned every snap-shooter into a photography artist. Mostly because the possibility of editing photographs has added to the overall complexity of digital photography. The process on the Digital Path is more complex, partly because there are so many opportunities to edit the captured image.

Photos of Natural Scenes and Outdoors.

We show in this paper that user engagement differs across different types of shared photo content. Specifically, we find significant differences between photos of natural scenes and other content types. On Flickr, photos of nature are 34% more likely to receive views, 32% more likely to receive comments and 16% more likely to receive favorites compared to all other types of photos. We also see that in general photos taken outdoors are more engaging, with 12% higher likelihood of being viewed, 16% higher likelihood of being commented on and 10% higher likelihood of being favorited.

The significant likelihood increase in engagement suggests that Flickr users are drawn and engaged to nature and outdoor photos. This might be a community specific behavior, especially since many of Flickr users are passionate about photography practices. On the contrary, photos of nature do not seem to encourage engagement when they are filtered. Filtered photos of nature are 18% less likely to be viewed, 36% less likely to be commented on and 22% less likely to be favorited. Similar to photos of nature, outdoor photos are less engaging when they are filtered. When outdoor photos are filtered, they are 23% less likely to be viewed, 38% less likely to be commented on and 35% less likely to be favorited.

This shows that Flickr users prefer the photos of nature and outdoors to be posted as original and not filtered. One possible explanation is that this type of photos are more appreciated when presented original rather than post-processed. Additionally, one could argue that the inherent value of these kind of photos is more visible when they are presented as original. Our findings here sheds light on the user base of Flickr and their preference in photography. Other photography based social sites might contain a community with less of a preference for raw nature; further research could begin to examine if that is the case.

Photos of Food and People

Photos of food content are highly likely to be engaging on Flickr. We find that food content are 34% more likely to be viewed, 32% more likely to be commented on and 16% are more likely to be favorited. This suggests that photos of food are highly engaging on Flickr, they are also 16% more likely to be viewed when they are filtered. Based on findings of this research we can design new features where the filters are suggested to the right type of content where it can improve engagement. Food blogging is a common practice on many platforms; here we find Flickr users prefer it and prefer it to be filtered (compared to nature photos which are equally likely to be viewed but do not fare well when filtered).

We also investigated how photos of people relate to engagement. Consistent with past research on Instagram (Bakhshi, Shamma, and Gilbert 2014), we find people photos experience a general engagement lift. Our results show that photos of people are more likely to be engaging on Flickr as well. They are 27% more likely to be viewed and 22% more likely to receive comments. This could be explained by the fact that humans are naturally drawn to faces and they like to view photos of themselves, their friends and even faces of strangers. Further, filtered photos of people are more engaging as well. Previous literature on domestic photography has shown that people like to construct images as one has wished to see them, often wishing to see them at their best (Chalfen 1987; Holland 2000; Musello 1979; Zuromskis 2009). This may be the explanation to why people filter their photos of people. Many of the photos of people taken by mobile camera are from self, family and friends and filters can help enhancing them. In short, photographs help us to construct our individual, family, and cultural identities as they appear to others (Chalfen 1987; Durrant et al. 2009; Musello 1979).

Photos of Text and Photos Taken in Low-light.

Our findings show that photos of text are not engaging on Flickr. These photos are 31% less likely to be viewed and 20% less likely to be commented on. Filtering such photos does not impose a positive effect. Filtered photos of textual content are 19% less likely to be viewed, 49% less likely to be commented on and 31% less likely to be favorited. A possible explanation can be due to community's interest. Photos that have text on them are usually post-processed for advertisement or communication through textual content. Flickr users are drawn to visual content and photography and the text added to photos usually degrades the visual value of the photo.

We also find that photos taken in low-light are less likely to be viewed (32%). Perhaps, this interest is due to difficulty of taking photographs in low-light by mobile camera technology. This is further dampened by the use of a filter where they are 26% less likely to be viewed, 49% less likely to be commented on and 35% less likely to be favorited. This could be related to the generally limited dynamic range of a low-light photograph. Most filters manipulate colors to add effects; photos taken in low-light are usually dark and so change of color might degrade the quality or result in more loss of details in the photo. This follows from past research, where distortions from filters lead to a drop in engagement with the exception of filters that make the image look historic with dust and scratches (Bakhshi et al. 2015). While not a low-light photo, an example of such distortions can be seen in Figure 1c, where the sky's gradient on the Chinchilla filter appears banded instead of smooth.

Implications and Future work

The practical implication of social engagement in online photo sharing lies strongly in search and recommendation. Our findings may shed light on how to filter, prioritize and highlight photos from the global photo stream, specially ones that have just been submitted and therefore haven't had time to accumulate very many likes and comments. Knowing photos with filters increase engagement suggests one could increase their search ranking to keep people on site and active. Additionally, one can think of further implications for increased understanding of images. Many research endeavors are looking into applications of image processing in smart systems (Yang et al. 2016b; 2016a). Our work can be used in driving engagement for similar smart systems.

Our results highlight the importance of effective methods that take advantage of filtered photos for personalization of site content. Additionally, we can take advantage of the findings of this research on various types of content, and customize filters based on the content. For example we know that filtered photos of food are more likely to be engaging while filtered photos of nature are less likely to attract user engagement. Based on these findings we can suggest filters on the right type of content.

This work opens a larger set of research directions and areas of investigation. Our work is based on observational data and we cannot make any causal claims. While we find that filtered photos have high chances of engaging users, we can't say how much of this effect comes from the context of the photo. Future work can also look at other visual characteristics of multimedia and study their impact on online behavior. It is also worth considering how filters are used in different contexts. For example, are people using highly saturated filters on photos of food, while using aging filters on human faces?

We find that photos with filters have higher chances of being viewed, commented on, and favorited on Flickr but we don't know if filters are the exact cause of this. We took a step further and evaluated the role of photo content. Our results show that filters impact different types of content differently. More experimental work needs to corroborate these findings.

Conclusion

In this paper, through a quantitative study, we uncover the role of content and filters in photography on the engagement that it receives. Our work is based on analysis of 4.9M Flickr images. While we verify that filtered photos are more engaging than non-filtered photos in general, this preference is not equally evident across different categories of content. Photos of food and people attract more engagement when filteres are used, while photos of natural scenes and photos taken at night are more engaging when left unfiltered. Our work provides various implications for design and theory of photowork online. Finally, this work describes engagement impact on Flickr and has shown to be similar to past work on Instagram; however, further investigation across other photographic sharing websites is needed to understand how community features affects social engagement.

Acknowledgments

Withheld for review.

Photo Credits

Withheld for review.

Change Summary (to be included elsewhere)

We thank the reviewers and editors for their review. Indeed we feel the article is stronger after accounting for their suggestions and revisions. In particular, we highlighted where our contribution lies in this paper (by the added analysis of content determined via AI) and how it extends previous work in the field. For example past work looked at people in photos or filtered photos. We now highlight where our findings are congruent with past research. Further, we highlight how our work takes filters, people, and other content into broader consideration with regards to engagement. We have extended the discussion around these combinatorial features as well as suggest new applications and follow up research.

Regarding the choice of the model (Negative Binomial over Poisson) and it's performance, we have explained in detail why we chose Negative Binomial. The main reason was that we saw over-dispersion in dependent variable in such situations Negative Binomial is a better fit for the data. For the performance, we also compared the final model with Null model and observed significant reduction in variance.

And, while we are aware of the YFCC100M, it does not contain engagement data. More so, it's unclear if CC data and public data receive similar engagement; hence we used our own public API crawl. But we mention this now in the discussion. We also have cleared our engagement dataset for publication and it will be made available with the publication.

Finally, we clarified the dataset, what is a photostream, some inconsistencies in language, and missing/miscited figures.

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