Analyzing and Recommending Photo Filters from Image Category and User Engagement Metadata

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***Index Terms*—photo filters, social engagement, filter recommendation, image category, image data, data analysis**

I. Introduction

Mobile phone photography & the use of photo sharing platforms have dramatically risen in popularity recently. Today, filters are chosen by users manually. We have identified this to hinder the social engagement of the users. Automatic filter recommendation can help improve the social engagement and visual appeal. This also has an unique side effect of users learning which filter suits their picture better based on metrics rather than chance.

Proposed Method and Survey: In this project we analyze filters on Instagram image data and find correlation between filters and various image attributes like category, period of day, season, location by weighing these features on engagement metrics (likes, comments). We propose to build a filter recommendation engine for images focused on engagement.

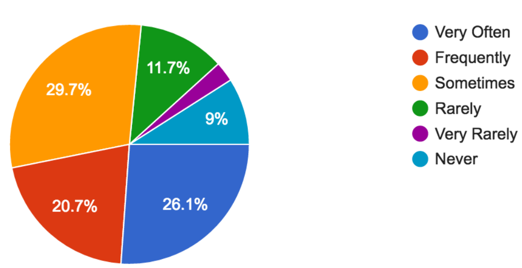

Fig. 1. Distribution of people getting confused while choosing filters.

Our initial research has shown that many users do not use the filters as it is cumbersome to go through the filter list. Our recommendations would definitely help such users to enhance their pictures and attract more social engagement. We performed an initial user survey to verify our hypothesis. The survey respondents were our friends, colleagues and relatives. Here are the results:

1) 77% people share photos on a social platform
2) 61% people apply filters on photographs before sharing
3) 76% people get confused between various filters.

Intuition: We study how filters are used in different image categories. As per our knowledge there is no current work that recommends filters to users based on the image category and various other image data. We propose a technique that will give informed recommendations to users by making use of previously unutilized information associated with an image. We also study how the application of our recommended filters to photos can change social behaviors like likes, comments, sharing etc with the help of visualizations.

II. Related Work

Hochman and Schwartz [1] shows a re-occuring spatio-temporal visual deviations during specific time period and place. Bakhshi et al. [2] analyzed how faces impact the engagement by using negative binomial distribution on likes and comment count[10]. Redi and Povoa [4] analyzed how filters affect image aesthetics.

Bakhshi et al. [6] studied the perception of filters through the eyes of producers and viewers for Flickr images and how filters affect user engagement. Ferrara et al. [3] studied topics and topicality in the Instagram network, relating it to user popularity. Hu et al. [7] identified 8 distinct image categories that are most popular on Instagram.

Hochman and Manovich [5] analyze the socio-cultural effects of specific places during specific periods of time on user uploaded photos. Hu et al. [9] quantifies various different properties based on the users and the images on Instagram which helps to gain insight about various meta-data and their distribution. Camila et al. [12] research focused on time of the day, week and its relationship to user behavior, resulting in new clustering strategies.

Hochman et al. [11] analyzed the volume, spatial patterns and aggregated visual features of photos from

Instagram to offer social, cultural and political insights. Highfield et al. [13] discussed methodology for research using Instagram data based on the learning on twitter which will help us understand the strength of these methods and their applications. Christian et al.[8] makes use of deep convolutional neural networks to solve the ImageNet classification problem.

III. Data Collection & Analysis

We have collected 600,000 images along with their meta-data per city using the Instagram APIs. A total of 2.4 million image dataset has been collected across 4 cities. The collected data has the following attributes :

id, link, tags, filter, comments, likes, latitude, longitude, locationname, locationid, createdtime, imageurl, userid, username, realname

Using the created time attribute we find out the stripped time from Unix timestamp and divide into month and hour of the day for inferring seasons and period of the day. To detect the image category we use a Deep Neural Network which categorizes images into 11 categories including *city, selfie, food, animal, flower, beach, nature, abstract, group, fashion and quote*. These initial set of categories are carefully chosen after analyzing a sample set of Instagram images and also several literature reviews.

A. Classifying images into categories

The ImageNet dataset consists of images belonging to 1000 different categories. The categories are varied but mainly consists of different types of animals, flowers, objects, clothing etc. We created a generic category class, for example a panda and a dog would be classified as an animal. We therefore fine-tuned the next to last layer and retrained the network to output 11 activation values which are then converted into probability values by the softmax layer which is the last layer of the network. Using a small dataset of about 150 to 500 images for various categories and by making use of random cropping, scaling, brightness and horizontal flipping we got an accuracy of about 88% on the test set which we also found to be reasonable on other arbitrary images from the instagram data collected.

B. Data Analysis

After the data preparation, we performed initial analysis on the images and found some patterns emerging from the data. Some interesting correlations and patterns are shown in Figures 2, 3, 4, 5.

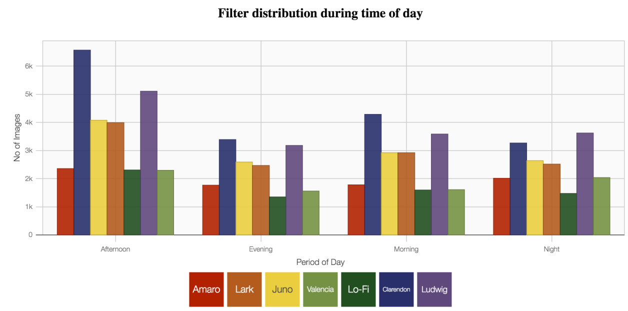

Fig. 2. Variation of filter usage during periods of the day. Clarendon filter is being widely used.

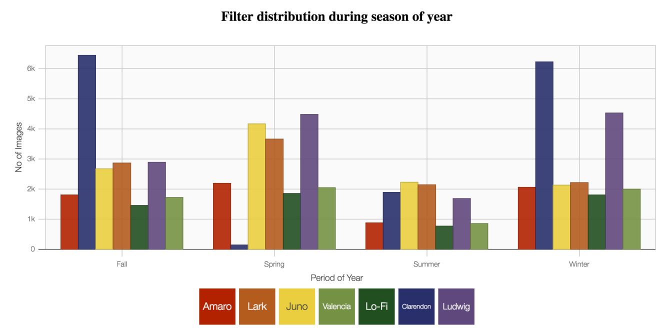

Fig. 3. Variation of filter usage during seasons of the year. Clarendon is more popular during Fall and Winter.

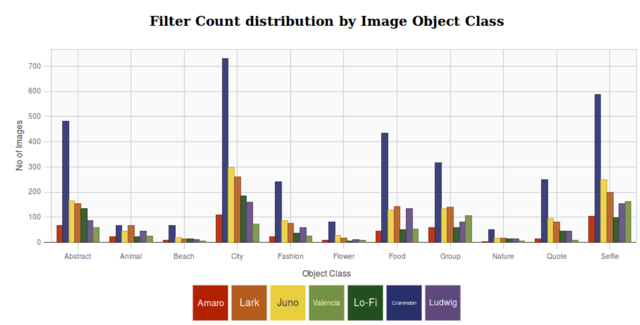

Fig. 4. Variation of filter usage by image class. City and Selfie are the most frequently photographed subjects.

IV. Solution & Implementation

A. Feature Construction

Based on the initial data analysis we found that the following features have the most impact on filter usage and social engagement.

1) Image Category
2) Season of the Year
3) Day of the week
4) Time of the day

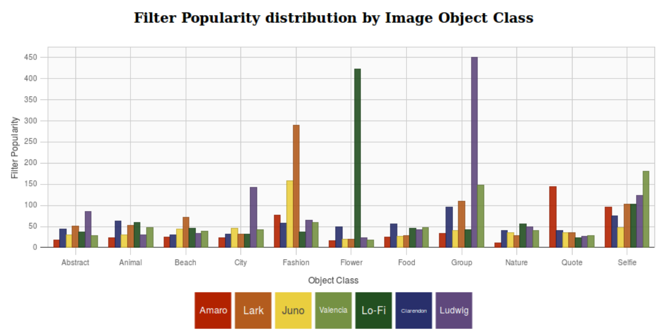

Fig. 5. Variation of filter popularity by image class. Popularity is obtained as $\frac{likes}{count}$. Using this we can see that most used filter may not be the most popular.

Our hypothesis about why these features might affect filter usage the most is due to surrounding conditions that affect photography aesthetics, like more ambient light during the day, longer days in summer etc. We also found that people use very different filters on Mondays than on other days. This indicates a social or work-life setting aspect to filter usage.

B. Recommendation of filters

We use KNN classifier to find the best possible filters for a given photo based on the distance metric over the features. Due to the sheer size of the data set, we often find that there are coincident data points and hence the number of nearest neighbors is kept dynamic. We take either all coincident points or 100 nearest points, whichever is higher. The distance metric is Euclidean distance:

$$d(x_i, x_j) = \sqrt[2]{\sum_{k=1}^{N}(x_{i,k} - x_{j,k})^2} \tag{1}$$

Then we do a weighted voting among the nearest neighbors as follows:

$$score(x_i) = (\alpha\mathcal{L}_i + \beta\mathcal{C}_i) * penalty \tag{2}$$

where α, β and penalty are hyper-parameters to weigh likes($\mathcal{L}$) and comments($\mathcal{C}$) respectively. The likes and comments obtained are normalized by the number of followers of that user. This is done to take into effect that likes/comments are proportional to the number of followers.

penalty : The position of filters in UI of Instagram app shows a trend in usage patterns. High usage is seen for filters that occur at the start of the list of filters. This can be justified using *Fitts' Law* [14][15] which states that human movement can be modeled by analogy to the transmission of information. Hence user tends to use the filter he sees first without scrolling through the rest. The *penalty* factor acts as a regularization parameter with filters being penalized according to the order in which they appear in the user interface.

Adding the reciprocal of the $score(x_i)$ to Eq 1 we get a modified distance metric

$$\begin{aligned} d(x_i, x_j) &= \sqrt[2]{\sum_{k=1}^{N}(x_{i,k} - x_{j,k})^2} + \frac{1}{score(x_i)} \\ &= \sqrt[2]{\sum_{k=1}^{N}(x_{i,k} - x_{j,k})^2} \\ &+ \frac{1}{(\alpha\mathcal{L}_i + \beta\mathcal{C}_i) * penalty} \end{aligned}$$

A higher score leads to a reduced distance and a lower score increases the distance. The nearest neighbors are then calculated based on this distance metric.

C. Architecture

The system design is as shown below in Fig. 6. It is clear from the architecture that we chose to adopt a 3-tier design : User - Instagram layer, Instagram - Amazon cloud, Amazon cloud - Visual Analytics, that includes the following process:

- Upload images to Instagram
- Get recent image from Instagram
- Visualize the dataset to observe trends
- Train the model on the image dataset and apply the train model to recognize the image and determine image class and extrapolate popular filters.

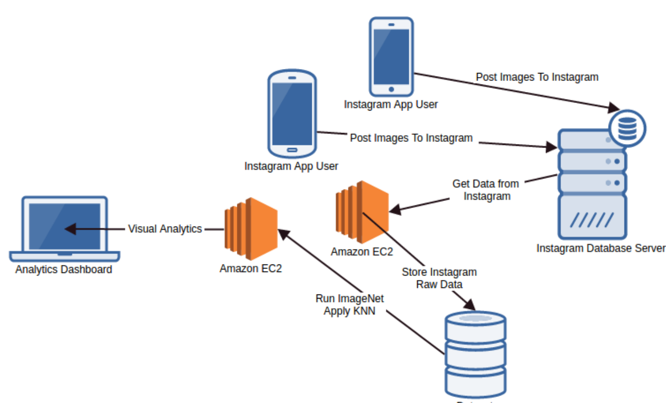

Fig. 6. System Design

D. UI and Visualizations

The User Interface design focused on giving recommendations based on the photo properties along with popularity of the recommended filters based on various attributes. It provides features to get an image directly from Instagram using the developer API and based on the image extracted the recommendation algorithm gives the top 5 recommended filters. The filters can then be applied to the image and the difference can be observed. The UI also shows popularity of the 5 filter based on the image category and also usage patterns based on period of the day and season of the year.

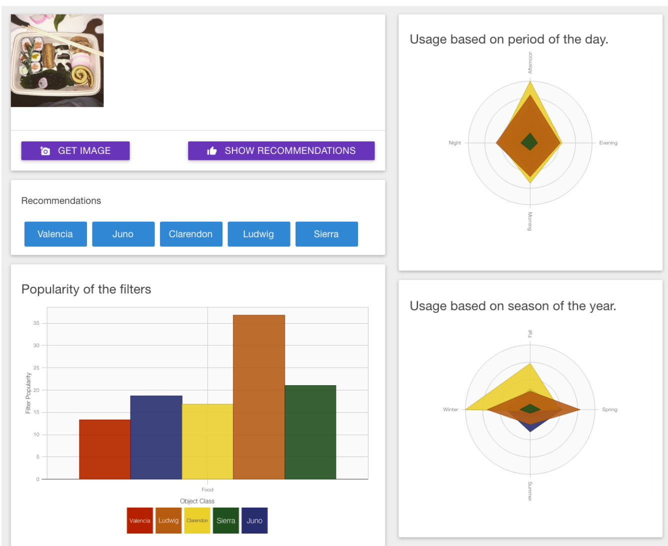

Fig. 7. Recommendation User Interface with aiding visualizations.

Users can also view the trends over the entire dataset. Figure 8.

For image rendering and applying filters over the images a open source image library called *Caman.js* is used. Visualizations are supported with *d3.js* library and overall UI uses Google Material Design scheme.

V. Evaluation & Results

Ground Truth : A User Survey of our recommended filters give us the ground truth. However this is not an entirely objective ground truth since a user likes a filtered image or not is quite subjective. We intend to take average user responses for the predicted filters.

We conducted user survey over 128 users and observed good results for our recommendation algorithm. Users were asked to choose between a random user applied filter and our recommended filter.

User surveys showed that for image category animal 80.2% and for category food 94.6% people like

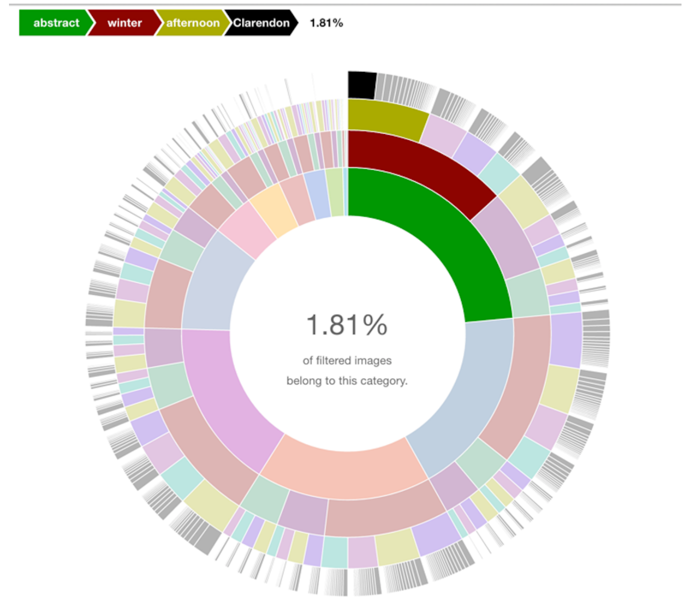

Fig. 8. Visualizing trends over the entire dataset

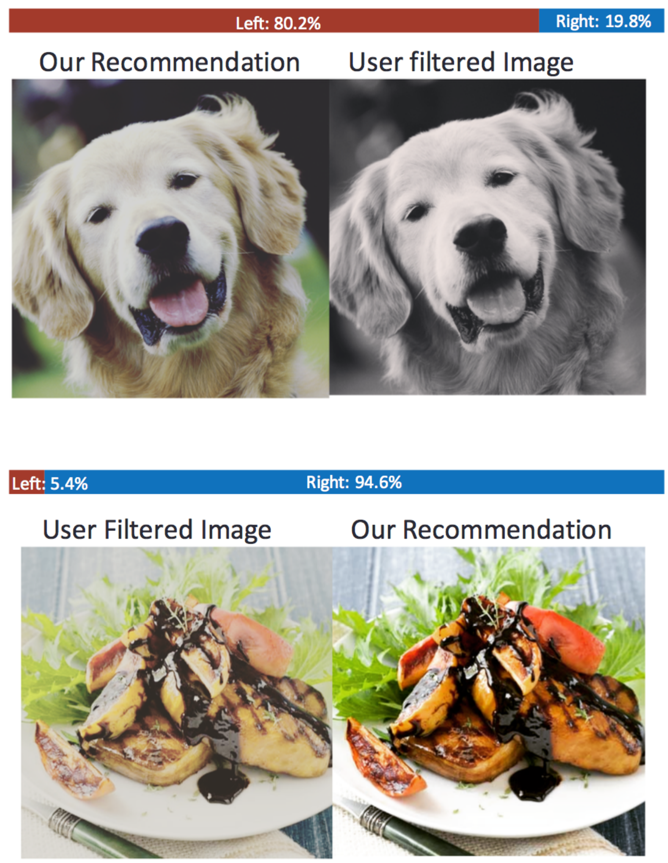

Fig. 9. User survey results showing comparisons of likes between our recommendations and user applied filters

our recommendation Fig 9. We similarly conducted the survey over other image categories like group(83.8% liked our recommendation), beach(51.4% liked our recommendation).

VI. Discussion & Conclusion

Our analysis and experimentation with image filters showed various patters emerging from the usage and also popularity of these filters. Using the Instagram image data our analysis showed that filter usage vary mainly upon the image category, time of day, day of week, season of year. Difference in usage patterns based on these features are due to difference in hue, brightness of the images.

Based upon these characteristics a K-Nearest Neighbor algorithm is used to recommend best filters. A modified distance function taking into account the user engagement towards a image is used to determine nearest neighbors. Top 5 filters are recommended. User survey on our recommendations showed that these filters enhance the image aesthetics and majority of the people liked the recommended filters over the user applied filters. In some categories our recommendations and user applied filters do not differ much in the vote counts they got. The possible reasons for this is that those categories did not have enough data points for proper training of the model and also due to the subjectivity of these studies. However with more training the recommender model can be improved to increase performance in all image categories.

This project shows that a good recommender system can be built for photo filters that will help users sharing photos on social platforms to enhance their images and increase user engagement. More work needs to be done to improve the quality of recommendations. Further experiments can be done by tweaking the KNN parameters and feature set. Other recommendation models along with hybrid models can be tried out for improvement.

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