Identifying User Profile Using Facebook Photos

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ABSTRACT
Apart from text messages, photo posting is a popular function of Facebook. The uploaded photos are of various natures, including selfie, outdoor scenes, food, etc. In this paper, we employ state-of-the-art computer vision techniques to analyze image content and establish the relationship between user profile and the type of photos posted. We collected photos from 32 Facebook users. We then applied techniques such as face detection, scene understanding and saliency map identification to gather information for automatic image tagging and classification. Grouping of users can be achieved either by tag statistics or photo classes. Characteristics of each group can be further investigated based on the results of hierarchical clustering. We wish to identify profiles of different users and respond to questions such as the type of photos most frequently posted, gender differentiation in photo posting behavior and user classification according to image content, which will promote our understanding of photo uploading activities on Facebook.

CCS Concepts
Human-centered computing → Collaborative and social computing systems and tools.

Keywords
Facebook, face detection, scene understanding, image tag, user profile analysis.

1. INTRODUCTION
In recent years, Facebook has become the most popular modern social networking service (SNS), and numerous photos are uploaded to Facebook by users every day. Facebook users can add additional information to uploaded photos, as shown in Fig. 1. These functions include: tagging friends in photos, writing description for the photo, "check-in" the location of where the photo, as well as replies to this picture, etc. Because of these interactive features, users are willing to upload photos to share with friends. Therefore, in the past, studies for user behavior pattern analysis or profiling related to Facebook are mostly based on observing their activity logs. However, such studies have rarely analyzed user behaviors from the content of the uploaded photos themselves. If we can make good use of the embedded information, we will be able to gain deeper understanding of the characteristics of users.

Figure 1. Photo-related functions in Facebook.

In this paper, we try to investigate user behavior pattern merely by their own uploaded photo content. Under our definition, the photos are first divided into the following categories: portrait, scene, theme, non-photorealistic, food, animal, text, and others. We also consider the composition of multiple photo classification, for example, "portrait" plus "theme" and "personal" will lead to "selfie". Finally, to meet the needs of qualitative research, we use a variety of criteria for profiling the user. Researchers can understand the Facebook population based on a single criterion, or they can profile a single Facebook user according to some combined criteria. With the proposed analysis, we wish to identify profiles of different users and respond to questions listed below:

1) Which type of photo is mostly uploaded by users?
2) How to obtain a more detailed, in-depth and comprehensive user profiling?
3) Are there any other sensible means of inspecting the photo collection?

The remainder of this paper is organized as follows. In Section 2 we outline related research. Section 3 elucidates our experiment process and methodology, as well as the indicators we used for evaluation. In Section 4, we respond to the above questions according to our user profiling. Section 5 concludes this paper and outlines future work.

2. RELATED WORK
Recently, advances in computer vision have enabled robust localization and identification of objects of interest in an image automatically. For example, ImageNet has hosted the annual large

IMCOM '17, January 05-07, 2017, Beppu, Japan

DOI: http://dx.doi.org/10.1145/3022227.3022267

visual recognition competition since 2010 [1]. The main missions include object detection and image classification. Accuracy of object detection has progressed from 0.23 to 0.62 in two years (2013 to 2015). Additionally, classification error has decreased from 0.28 to 0.036 during the same period. Such high accuracy rate has made automatic tagging of photos possible without human intervention.

More recently, Facebook AI Research team published their object detection framework known as Multipath in [2]. It is modified from the standard Fast R-CNN architecture. A pipeline containing segmentation and object detection has been formulated to allow smaller objects to be discerned. Compared to the baseline Fast R-CNN detector, their proposed Selective Search method showed an improvement over 66%. Because the project is open source, it is ready to be employed to analyze the content of photos with good accuracy.

Study of photo posting on social media has been done previously. Hu *et al*. proposed a method to label Instagram photos as one of the following eight categories (Friends / Food / Gadgets / Captioned Photos / Pets / Activities / Self-portraits / Fashion) according to the content [3]. They also classify users into 5 groups by the type of their posts. Different clusters represent different profiles, such as those who like to upload selfie tend to add text on it. Our study follows a similar categorization. Instead of manual classification, however, we introduce computer vision technology to analyze photo information automatically. More data can be analyzed with faster processing speed. The result of classification by content is also more stable. We outline the main differences between Hu's work and our research in Table 1.

Table 1. Comparison with Hu's approach

Items	Hu, et al. [2]	Ours
Classification	Manual	Automatic
# of photos	1000 photos	12218 photos
Speed	Slow	Fast
Stability	Loose standards	Consistent standards

3. THE PROPOSED METHODOLOGY

In this section, we will introduce the proposed user profile identification system. As illustrated in Fig. 2, it includes 4 processing stages: 1) Images analysis, 2) Tag reduction, 3) Photo classification, and 4) Users clustering. Details of each stage are described below.

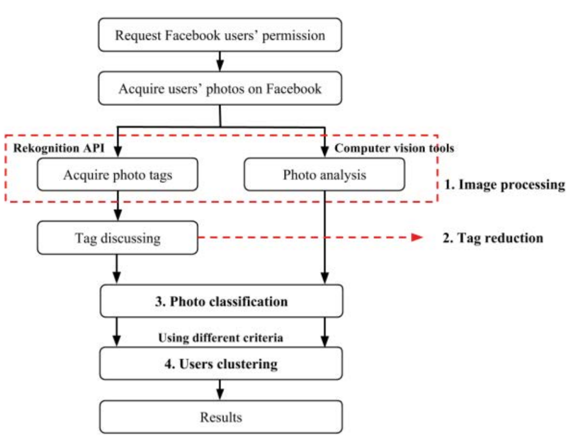


Figure 2. Proposed method for identifying user profile.

3.1 Image Analysis

After collecting photos using Facebook API from the participants, we enter the image processing stage. We employ three tools to retrieve information from images.

1) Face++ API [4]: We use Face++ API to identify the faces and related information in an image. The API not only provides face size, position but also age, gender, wearing glass or not, race, and smiling index, as shown in Fig. 3. In our system, we make use of two attributes in a photo: number of detected face, and gender of each face.

2) Rekognition API [5]: We use Rekognition API to identify people's faces, scenes and objects from images, as shown in Fig. 4. The API returns multiple tags associated with the photo with a confidence score between 0 and 1. In order to acquire enough information, we set the API to generate ten tags for an image. In our research, we obtain the tags from an image, and confidence score of each tag.

3) Saliency map [6]: Significant visual area can be extracted by image features including color, orientation, brightness variation and movement. Fig. 5 shows an example of calculated saliency map. This information is later employed in the classification of 'theme' photo, indicating a main subject is present in the photo.

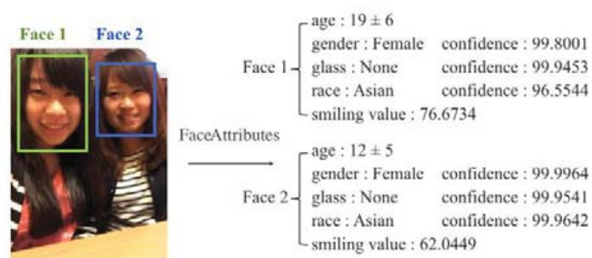


Figure 3. Obtaining face attributes using Face++ API.

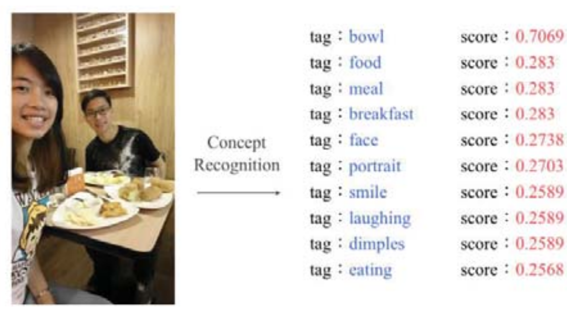


Figure 4. Tag extraction by Rekognition API.

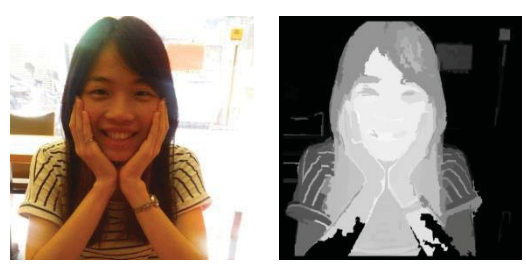


Figure 5. Saliency map.

3.2 Tag Reduction

We obtained the top ten tags of an image using Rekognition API. Depending on the image content, some tags receive very high confidence scores while others are included since we use ranking instead of score for filtering. Out of 12218 photos we analyzed, 2119 distinct tags have been generated. However, some tags have similar meanings. Some tags exhibit low confidence scores. Some tags occur quite infrequently. The following reduction scheme is devised to keep only important tags.

1) Filtration: Firstly, we keep the top 7 tags for an image. Then we set up a threshold to remove the other 3 tags which have lower confidence score than the threshold (set to 0.3 in our study).

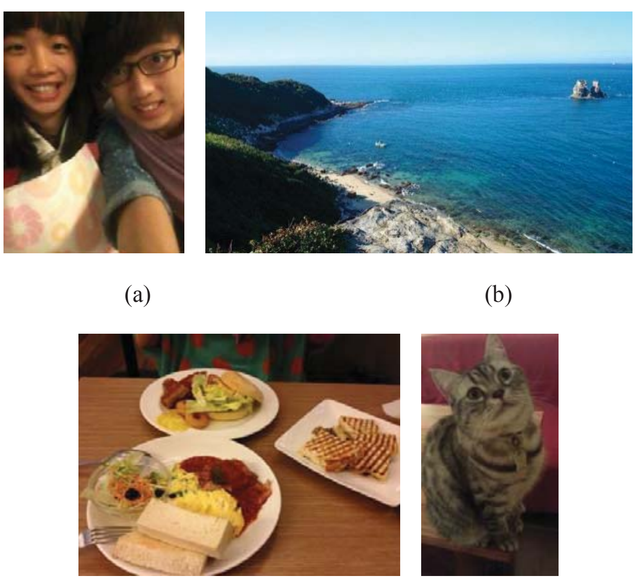
2) Tag classification and merging: Because many tags have similar meanings, such as "woman", "female", "girl", "lady"; or "text", "font", "label", "word", "document", therefore, we have to combine those tags with similar meanings into a single tag. Following the above the steps, tags appearing more than 35 times are retained, generating a total of 552 tags. The number of tags in each category are listed in Table 2.

Table 2. Tag classification

Category	Portrait	Scene	Non-photorealistic	Food	Animal	Text	Plant	Item	Ots.
# of tags	141	190	9	53	14	20	27	44	54

3.3 Photo Classification

As mentioned in the introduction section, we divide photos into 8 categories, and use the classification results as features. Fig. 6 presents examples from each category. We give more detailed definition for each category in the following.



(a) (b)

(c) (d)

(e) (f)

(g) (h)

Figure 6. Examples from each category. (a) portrait (b) scene (c) food (d) animal (e) theme (f) text (g) non-photorealistic (h) others.

3.3.1 Portrait

The way we classify a photo as portrait is by checking the number of human faces and gender. The category can be further divided into "personal", "opposite gender", "small group", and "big group" photo, according to the number of people and gender detected, as illustrated in Fig. 7.

Besides, some users like to use a part of the body, such as hands or feet, as if they appear in photos. Sometimes the background makes face detection difficult. In these cases, the obtained tags from previous stage can be used to determine if the picture is a portrait.

(a) (b) (c) (d)

Figure 7. Examples from sub-categories of portrait. (a) personal (b) opposite gender (c) small group (d) big group

3.3.2 Scene

We only classify photos as scene according to obtained tags. If the picture is taken indoors, we usually see tags such as "room", "restaurant", "bed", or "furniture"; while given outdoors pictures we may have tags like "sky", "ocean", "architecture", or "bridge", etc.

3.3.3 Theme

Saliency map is utilized for classifying theme photo. The criteria are defined as follows: region of strong saliency response has to exceed a certain percentage. In this research, the threshold for saliency value is set to 64 (1/4 of the total range) and the minimum percentage is set is set to 33.3% (1/3 of the whole area).

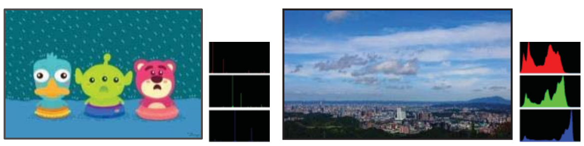
According to our criteria, Fig. 8-(a) will be classified as a 'theme' photo.

(a) (b)

Figure 8. Two saliency maps for caculating visually significant area. (a) 62.46% (b) 14.54%

3.3.4 *Non-photorealistic*

Non-photorealistic photos are usually produced by single or limited colors, so that specific values are usually particularly prominent in color histograms; while other kinds of photos do not have this characteristic in color histograms, as shown in Fig. 9. Therefore, we consider photos as non-photorealistic by using the characteristic of RGB histograms. We also rely on tags such as "collage", "sticker" to determine if a photo is non-photorealistic.



(a) (b)

Figure 9. RGB histograms. (a) non-photorealistic (b) scene image

3.3.5 *Food*

We classify photos as food according to obtained tags. Examples include "food", "meal", "cake", and "drink".

3.3.6 *Animal*

We classify photos as animal according to obtained tags. Examples include "animal", "mammal", "dog", and "cat".

3.3.7 *Text*

We classify photos as text according to obtained tags, Examples include "text", "word", "logo", and "signature".

3.3.8 *Others*

All photos which cannot be classified as one of the foregoing categories belong to this class.

3.4 User Clustering

In order to separate users into different groups, we use hierarchical clustering [7] to calculate the distance between user features. Through polymerization (bottom-up) or split (top-down) two ways, hierarchical clustering makes smaller clusters which have high degree of similarity merge into larger clusters, or larger clusters split into smaller clusters. Here we adopt polymerization, as shown in Fig. 10. By using dendrogram, we can generate corresponding clustering number flexibly. For example, if we require three clusters, and we set the threshold between t4 and t5, then we will get three clusters that contain (A,B,C), (D,E) and (F,G), respectively.

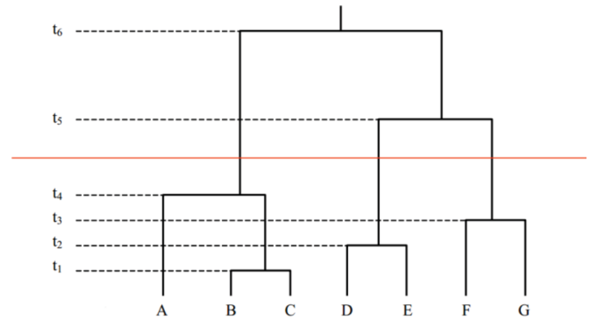


Figure 10. Dendrogram structure.

After photo classification at the previous stage, we then calculate the following 4 types of features for user clustering:

1) Proportion of category: In order to reduce the impact of the number of photos, we compute the proportion of all photos of the user in 8 categories in Eq.(1):

$$\text{Proportion}_{\,category} = 100 \times \frac{\text{Count}_{\,\text{category}}}{\text{Count}_{\,all\ categories}} \quad (1)$$

Therefore, the sum of the 8 features is 100.

2) Average count of category: The average count of each category per photo of the user can be calculated according to Eq.(2):

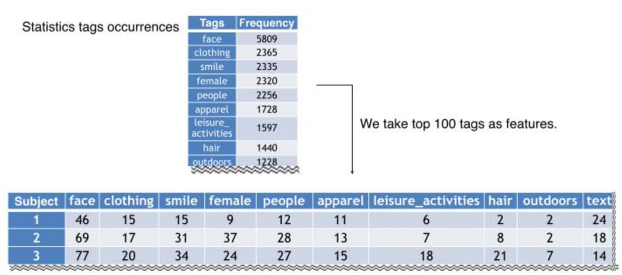
$$Average\ Count_{category} = \frac{Count_{category}}{Count_{photo}} \quad (2)$$

The range of this feature is between 0 and 1. A value closer to 1 indicates that the user posts pictures mostly from this category.

Additionally, the sum of these 8 features (one average count from each category) represents how many categories are present in each photo. We can examine if a photo belongs to a single category or multiple categories.

3) Proportion of portrait type: We take the proportion of 4 subcategories of portrait and others without portrait as 5 features. The sum of the 5 features is 100.

4) Count of tags: We sort the number of occurrences of the 552 tags after tag reduction and keep the top 100 tags. We then use the count of the 100 tags from users' photos as features, as shown in Fig. 11.



Tags	Frequency
face	5809
clothing	2365
smile	2335
female	2320
people	2256
apparel	1728
leisure_ activities	1597
hair	1440
outdoors	1228

Subject	face	clothing	smile	female	people	apparel	leisure_activities	hair	outdoors	text
1	46	15	15	9	12	11	6	2	2	24
2	69	17	31	37	28	13	7	8	2	18
3	77	20	34	24	27	15	18	21	7	14

Figure 11. Use top 100 tags as features.

4. RESULTS AND DISCUSSION

We gather 32 Facebook users (including 16 males and 16 females), which are most of students. Fig. 12 shows the number of photos posted by different users. Table 3 shows the general statistics. We observe that females tend to post more photos than males. Furthermore, numbers of photos posted by males have a greater variance than those by females.

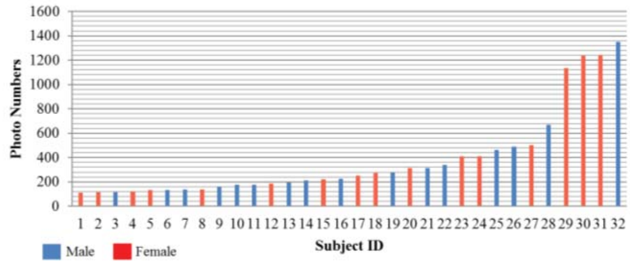


Figure 12. Facebook users' data after sorting.

Table 3. Facebook users' photos general statistics

	Photo Number	Average	STD
Males	5427	339.19	391.62
Females	6791	424.44	300.059
All	12218	381.81	351.45

4.1 Which kind of photo is mostly uploaded by users?

We compute the total number of photos in each category firstly. After normalization, we draw the pie chart as shown in Fig 13. The chart indicates that people tend to post portraits photos. If we further divide portraits into four sub-classes, we can observe in Fig. 14 that the majority of photos are "personal" and "small group", while "big group" photos are relatively few.

We control gender factor and observe the result in Fig. 15 and 16. Figure 16 shows that female tend to post photos of small group and opposite gender, while male tend to post photos of non-portrait. However, Fig. 15 shows no significant difference between gender groups. We think that is because there are also different types in both groups, and the sum of these sub-groups will reduce the difference for gender factor. Therefore, we will analyze user behaviors based on features extracted from photos directly.

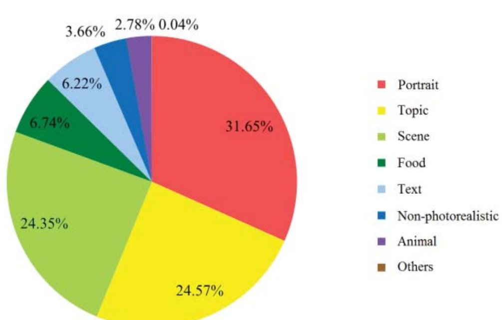


Figure 13. Classification of photoscollected from all users.

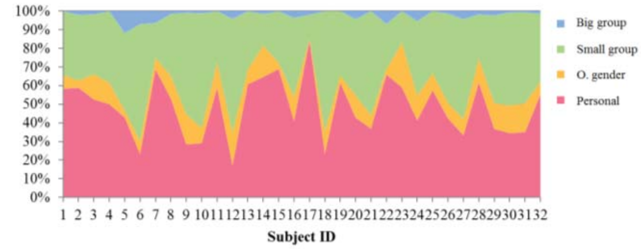


Figure 14. Subcategories of portraits of all users.

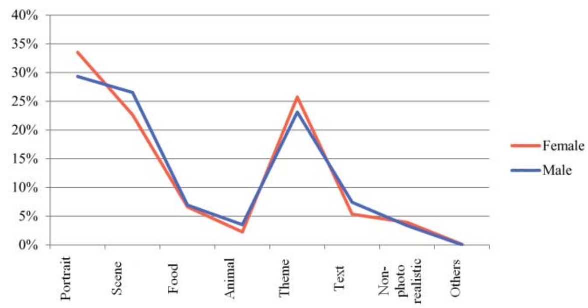


Figure 15. Gender comparison with proportion of category.

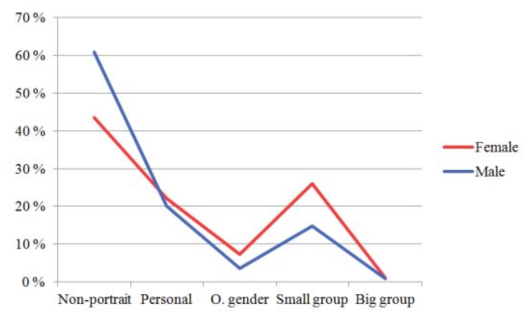
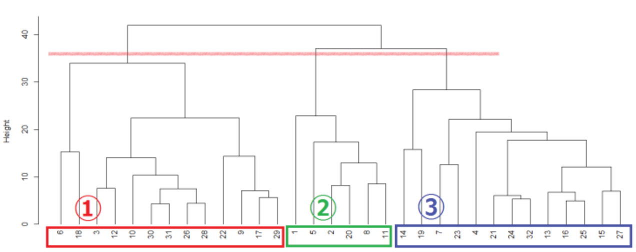


Figure 16. Gender comparison with proportion of portrait type.

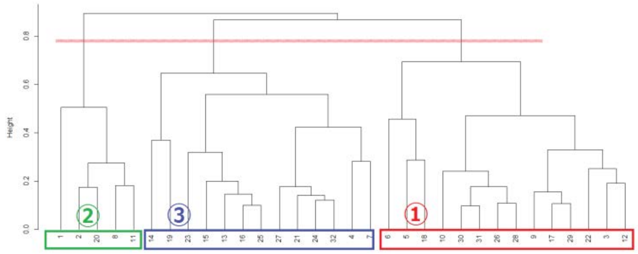
To sum up, portraits are mostly uploaded by users. And within the portraits category, female prefer post "personal" and "small group" photos, while male tend to post "personal" photos for the subjects studied in this work.

4.2 How to obtain a more detailed, in-depth and comprehensive user profiling?

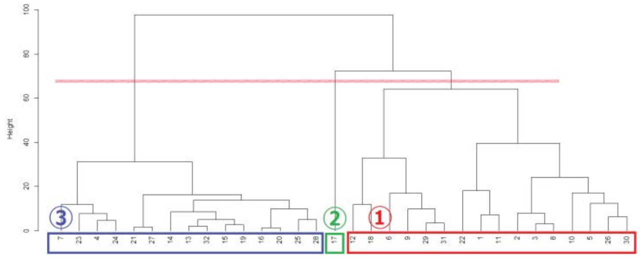
Here we want to discuss the aforementioned four different criteria for user clustering as follows: 1) Proportion of category, 2) Average count of category, 3) Proportion of portrait type, and 4) Score of tags. Fig. 17 shows the four clustering dendrograms.



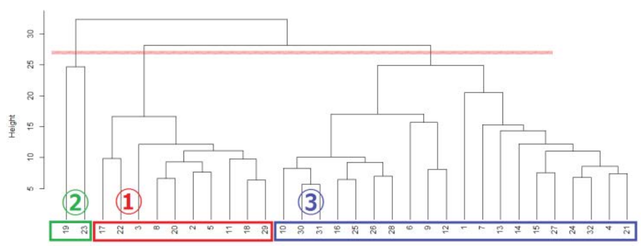
(a)



(b)



(c)



(d)

Figure 17. User clustering dendrograms. (a) proportion of category (b) average count of category (c) proportion of portrait type (d) count of tags

4.2.1 Proportion of category

Table 4 shows the details in each cluster. Fig. 18 illustrates the distribution for each cluster.

According to the result, we discover that users in cluster 1 post mostly portrait photos. Users in cluster 2 post higher proportion of text and non-photorealistic photos, while users in cluster 3 post scene photos mostly.

Table 4. User clusters by proportion of category

	Subject ID
Cluster 1	3, 6, 9, 10, 12, 17, 18, 22, 26, 28, 29, 30, 31
Cluster 2	1, 2, 5, 8, 11, 20
Cluster 3	4, 7, 13, 14, 15, 16, 19, 21, 23, 24, 25, 27, 32

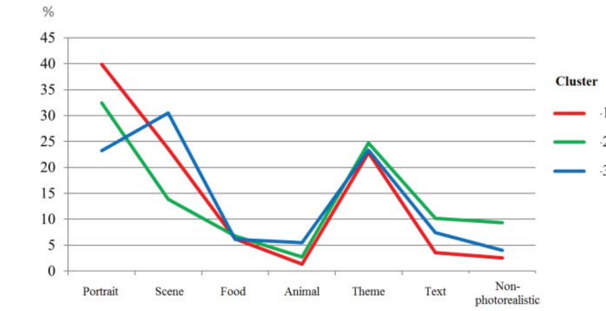


Figure 18. Proportion of category comparison with 3 clusters.

4.2.2 Average count of category

Detailed results are shown in Table 5. We observe that the two results are almost the same except for user 5, which moved from cluster 2 to cluster 1. Table 6 illustrates the two features of this user.

Table 5. User clusters by average count of category

	Subject ID
Cluster 1	3, 5, 6, 9, 10, 12, 17, 18, 22, 26, 28, 29, 30, 31
Cluster 2	1, 2, 8, 11, 20
Cluster 3	4, 7, 13, 14, 15, 16, 19, 21, 23, 24, 25, 27, 32

Table 6. Comparison proportion and average count for categories, using data of User 5

	Portrait	Scene	Food	Anim.	Theme	Text	N-R.	Ots.
Pro-portion	39.78	16.42	6.2	1.82	16.42	8.39	10.95	0
Avg. count	0.83	0.34	0.13	0.04	0.34	0.17	0.23	0

We found that it depends on the average categories for each photo posted by the user. Take User 5 for example, 2.08 categories are contained in each photo. If the average numbers of categories in each photo between users' data are closer, proportion and average count are also similar. Conversely, the difference will be amplified.

4.2.3 Proportion of portrait type

Detailed results are shown in Table 7. Fig. 19 illustrates the proportion of each sub-category. We can find some users have moved to other clusters, but the two major clusters remain substantially unchanged. Cluster 1 may correspond to cluster 1 of 4.2.2, users who prefer portrait. Analysis of sub-category indicates that they all tend to post small group photos. Cluster 3 is consisted of users who prefer non-portrait (scene) photos.

Table 7. User clusters by proportion of portrait type

	Subject ID
Cluster 1	1, 2, 3, 5, 6, 8, 9, 10, 11, 12, 18, 22, 26, 29, 30, 31
Cluster 2	17
Cluster 3	4, 7, 13, 14, 15, 16, 19, 20, 21, 23, 24, 25, 27, 28, 32

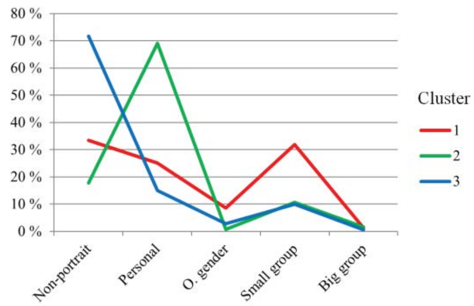


Figure 19. Proportion of portrait type in three clusters.

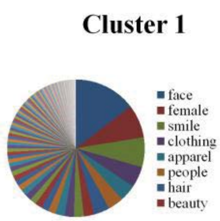
It is worth noting that User 17 exhibits a strong preference in posting personal photos. In the previous clustering, this subject has been assigned to cluster 1. Due to the features of sub-categories of portrait, this user's preference can be highlighted.

4.2.4 Count of tags

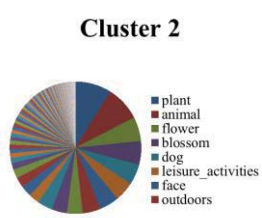
Table 9 shows the clustering result. Fig. 20 presents the clustering result of tag profiling.

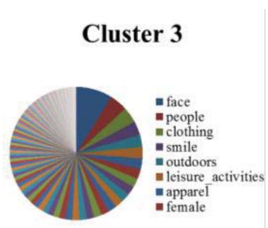
Table 9. User clusters by count of tags

	Subject ID
Cluster 1	2, 3, 5, 8, 11, 17, 18, 20, 22, 29
Cluster 2	19, 23
Cluster 3	1, 4, 6, 7, 9, 10, 12, 13, 14, 15, 16, 21, 24, 25, 26, 27, 28, 30, 31, 32



(a)





(b) (c)

Figure 20. Tag profiling. (a)-(c) shows the structure of cluster 1-3, respectively.

We observe that users in cluster 1 post portrait pictures mostly, users in cluster 2 tend to post plant and animal photos, while users in cluster 3 tend to post portrait and scene photos. Because tag profiling is more specific, results of tag-based clustering are different from those obtained using other features. In other words, it provides a different perspective in characterizing the user profile.

4.3 Are there any other sensible means of inspecting the photo collection?

We use webpage to demonstrate our experimental results as shown in Fig. 21. It is rather simple to combine existing data to develop an image browsing system. The website can provide some functions such as automatic filtering and charting. It is designed to facilitate researchers who focus on the qualitative aspect of the user profile.

Figure 21. Prototype website.

5. CONCLUSION

Unlike most of previous studies, we conducted user profile analysis based only on photos uploaded by users. In this paper, we propose methods to retrieve image information based on the result by computer vision and machine learning techniques to represent user preference in posting Facebook photos. We propose eight photo categories, along with the corresponding classification methods. We also investigate how the selection of features affects photo classification and the subsequent user clustering and profiling. The tools developed in this work serve the purpose of understanding user behavior from both quantitative and qualitative perspectives.

6. ACKNOWLEDGMENT

This research was supported by the Ministry of Science and Technology, Taiwan, grant number: 102-2420-H-004 -046 -MY3.

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