修　士　論　文

Brand Relationship and User Preference Analysis on Social Media

(ソーシャルメディアを用いた
ブランド関連性と消費者選好の解析)

指導教員　山﨑 俊彦　准教授

東京大学大学院
情報理工学系研究科
電子情報学専攻

氏 名　48-176440　張　軼威

提 出 日　　2019 年 1 月

Abstract

Social media has become a significant part of our modern civilization. This phenomenon also widely affecting advertising industry by influencing user preference. Since understanding users' behavior on social media can greatly affect the trends in sales, social media marketing is becoming more and more popular for researchers.

In this thesis, we begin with analyzing how certain products or services are posted on Instagram, a photograph based social network, and how trends evolve by analyzing tags and image features. We also analyze temporal evolution of certain tags, which can provide different perspectives when analyzing certain products.

We further investigate whether content on social media could reflect customers' behaviour in real-world. Nowadays, brands are using social media such as Instagram regularly for marketing and targeted advertising. Different from traditional advertising paradigm, we are able to analyze customers in a more direct way. We propose a new scale for measuring the similarity between brands by analyzing tags and images uploaded by brands' followers. In the evaluation, we use two real-world co-purchasing data to create customers' co-purchasing results. And by taking questionnaires on Yahoo! crowdsourcing, we obtain users' co-purchasing and interest tendencies. We evaluate our results by comparing with the real-world co-purchasing logs and questionnaires' results. We hypethesize that our proposed methods can be used to predict customers' preferences.

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1. Social Media

Social media refers to Internet-based applications which build on the ideological and technological foundations of Web 2.0. It allows the creation and exchange of user-generated content [1]. Users can share their ideas, images, videos and also interact with other users. Social media is already a part of people's everyday life. For example, around 500 million tweets are tweeted on Twitter per day [2]. 350 million photos are uploaded to Facebook every day [3]. Instagram's service grown to more than 800 million registered users in September 2017, with 500 million users using it every day [4]. YouTube has over a billion users. Users collectively watch a billion hours of video each day, generating billions of views [5].

1.2. Study of Online Content

The term online content can be defined as any type of information on websites. It can refer both to the subject of the information and the individual item used to deliver the information. Tatar et al. defined online content as any individual item publicly available on a website in the form of text, image, audio or video [6].

Nowadays, generating online content has become popular since it is very easy and costless, resulting in a world saturated with information. It makes the prediction of social popularity has profound impacts, since it offers useful information and business opportunities. Szabo and Huberman predicted popularity of Youtube videos after their publication [7]. Khosla et al. used Support Vector Regression

to predict popularity of Flickr photos before they are published [8]. They combine content features and social cues in order to understand the importance of photo content. Piotrkowicz et al. used headlines to predict the popularity of news articles on Twitter and Facebook [9].

Recommendation is another hot topic in the study of social media both commercially and in the research community. Big data increasingly benefit tasks of recommendation and make personalized recommendation become available. Content on social has been widely used in travel recommendation [10, 11], movie recommendation [12, 13], fashion recommendation [14, 15] and item recommendation on shopping sites [16].

1.3. Social Media Marketing

Due to the rapidly increased popularity of social media, a new marketing approach has emerged. Social media marketing is the use of social media platforms and websites to promote a product or service [17]. By 2018, 91% of the Fortune 500 companies are actively using Twitter, 89% are actively using Facebook, 63% have corporate Instagram accounts [18]. It is already a trend to use social media to connect with consumers. Companies make use of platforms such as Facebook, Twitter and Instagram to reach audiences much wider than through the use of traditional advertisements such as newspaper, television and radio.

With these newfound trends, we can analyze the effect of posts on customer behavior. These data can be utilized to analyze implicit relationship between brands, and recommend items to users. It has the potential to provide a brand new approach to interact with customers. Customers can review the product in a more direct way and companies can receive opinions more promptly.

1.4. Purposes and Contributions

We investigate the relationship and similarity between brands using the content derived from social media platforms. Also, we try to establish that users'

preferences can be detected from social media. Understanding relationship between brands, products and people can have profound effect on marketing. For example, when a brand wants to find celebrities for endorsements, it is important to consider whether his/her followers are potential customers to its products. Similarly, when a shopping mall want to choose the brands they want to carry, which combination has the potential to attract more customers is a lucrative proposition.

We briefly summarize the main contributions and findings as follows:

- We analyze several product-related tags on social media. We propose a clustering method in order to discover meaningful subsets of related images.
- We analyze and discuss temporal evolution of several product-related tags on Instagram.
- We present an approach to predict similarity between brands using tags and images from brands' followers.
- We compare several features that might help us understand brands' similarity inculding images from the brand, images from users and tags from users.
- We create two evaluation datasets base on two real-world customers' purchasing history. We evaluate our proposed methods by comparing with the real-world customers' purchasing history.
- We take questionnaires via Yahoo! crowdsourcing in order to obtain users' co-purchasing and interest tendencies. It also provides anther evaluation angle besides point card and credit card purchasing history.
- In order to further evaluate our proposed methods, we compare results based on proposed methods with users' co-purchasing and interest tendencies from questionnaires.
- We investigate several methods for tag selection with accuracy as the end goal. Our work reveals that tag feature is much powerful than image feature in similarity prediction.

- In this evaluation, we prove that our proposed methods can be used to predict customers' preferences.

1.5. Organization of This Thesis

This thesis is organized as follows. We begin by introducing product popularity analysis in Chapter 2. Chapter 3 presents the analysis of brands' relationship. Chapter 4 concludes this thesis and suggests directions of our future work.

Chapter 2

Products' Popularity Analysis

2.1. Introduction

Billions of photographs are uploaded to the Internet every day, through various photo and video sharing services. Social media is already a part of people's everyday life. Instagram is a portal which allows people to share photos and videos. Since its launch in October 2010, Instagram has had a meteoric rise. According to the latest statistics, the service has a user base of more than 800 million registered users in September 2017 [4]. There are lots of images using the same tag, but they may refer to completely different visual concepts. We apply image clustering in order to discover meaningful subsets of related images. Then, we analyze clustering results and temporal evolution of these tags.

2.2. Related Works

In the past few decades, analyzing why content on social media becom popular has been a popular topic [19, 20]. Hessel et al. focused on predicting popularity of pairs of submissions posted to Reddit within 30 seconds in order to separate the time effects [21]. Wu et al. showed that social media popularity changes over time and often exhibits varying temporality across different time scales [22, 23, 24]. They showed that time matters a lot on social media. We want to investigate temporal evolution of certain tags, which can provide different perspectives when analyzing certain products or services.

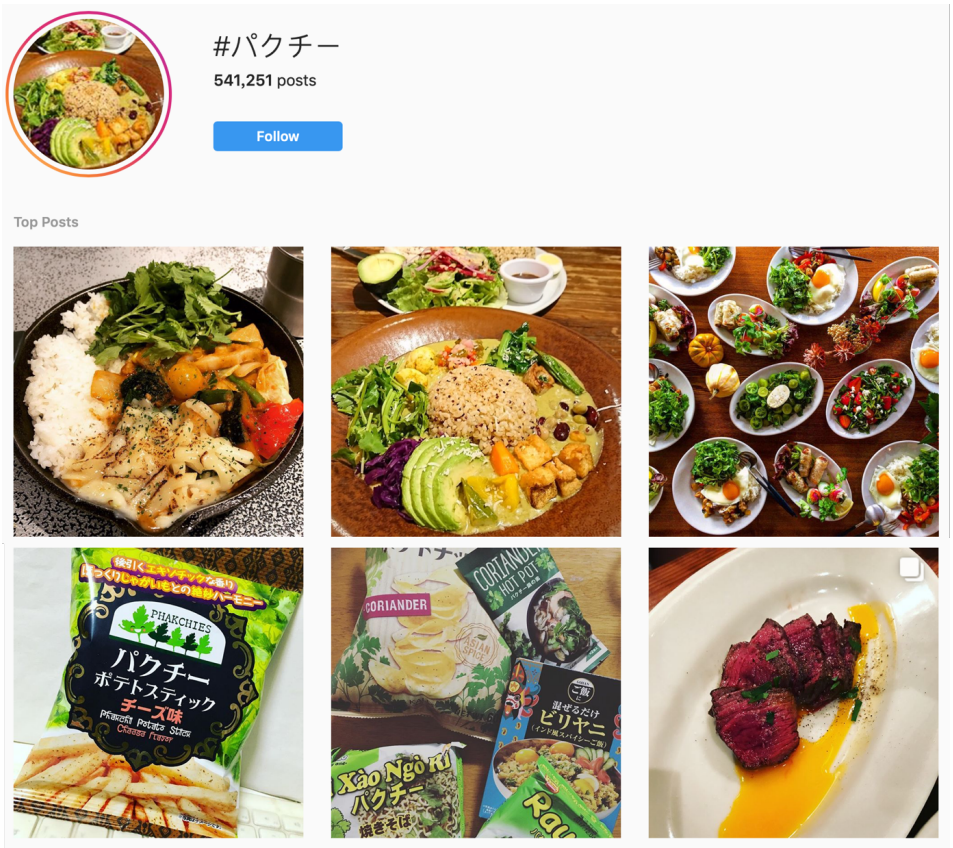


FIGURE 2.1 – Example of images taged "coriander".

A problem of analyzing data on social media is that user's description itself could have several meanings. For example, when searching hashtag "coriander" on Instagram, majority of users would perhaps associate the hashtag to spices. We found that under the same tag, there are different types of images. Other than its use as a spice, the tag also refers to "coriander specialty restaurant", "coriander dessert" and "coriander potato chips". We show some sample images in Figure 2.1. Description has several meanings make data analysis difficult. For example, it become hard to find out the popularity evolution of coriander-flavored packaged foods.

2.3. Image Clustering and Class Discovery

We previously discussed the situation of images attributed with a generic tag; these were demonstrated to refer to different meanings. In this section, we attempt to separate the images into different visual categories.

Using "coriander", "acai" and "pocky" as example. We collected images with these tags for analyzing.We choose a 50-layer ResNet [25] pretrained on ImageNet [26] to extract deep features from these images. We use mini-batch K-means [27] as the clustering method since it is considered as the gold-standard clustering method. In Figure 2.4, we show clustering results for K = 5.

Images are successfully separated into several meaningful subsets by the clustering. Taking Figure 2.2 as an example, when the size of the cluster is 5, label 0 shows food with few coriander; label 1 shows coriander itself or food items containing coriander; label 2 shows menu images and images including people, which might be further separated into two classes; label 3 shows products using coriander appeared in recent years; label 4 shows coriander salad or dessert.

Using the tag "acai" as an example, in Figure 2.3, we show images posted to Instagram when the cluster size is 5. Label 0 shows image with people; label 1 shows food items containing acai; label 2 shows products using acai; label 3 shows acai smoothie, which is a popular cold drink in summer; label 4 shows acai salad or dessert.

Using the tag "pocky" as an example, in Figure 2.4, we show images posted to Instagram when the cluster size is 5. Label 0 and label 1 both show images with pocky; label 2 shows images with people; label 3 shows images with animals; we think label 4 shows images not related to pocky itself. This clustering technique can thus help us segregate the images.

2.4. Temporal Evolution

Temporal evolution is the attribute of a data item evolving over time as a function of one or more paramters. Since time matters a lot on social media, we want to make a time-series from the data. We think temporal evolution of certain tags can provide different perspectives when analyzing certain products or services.

We use tag "coriander" as the example. In Figure 2.5, we show the number of images posted to Instagram each month as a log-linear plot. Coriander is

(a) Label=0

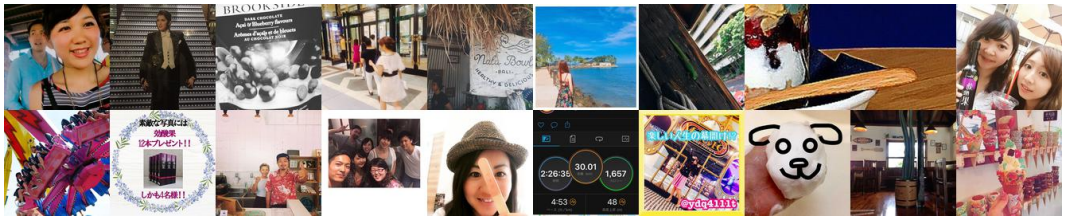
(b) Label=1

(c) Label=2

(d) Label=3

(e) Label=4

FIGURE 2.2 – Clustering result of the tag "coriander" when K = 5.



(a) Label=0

(b) Label=1

(c) Label=2

(d) Label=3

(e) Label=4

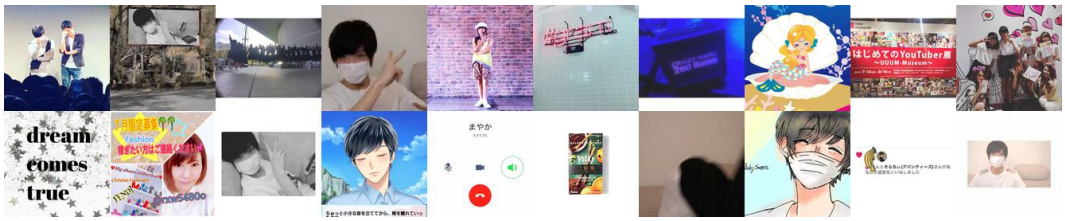
FIGURE 2.3 – Clustering result of the tag "acai" when K = 5.

(a) Label=0

(b) Label=1

(c) Label=2

(d) Label=3



(e) Label=4

FIGURE 2.4 – Clustering result of the tag "pocky" when K = 5.

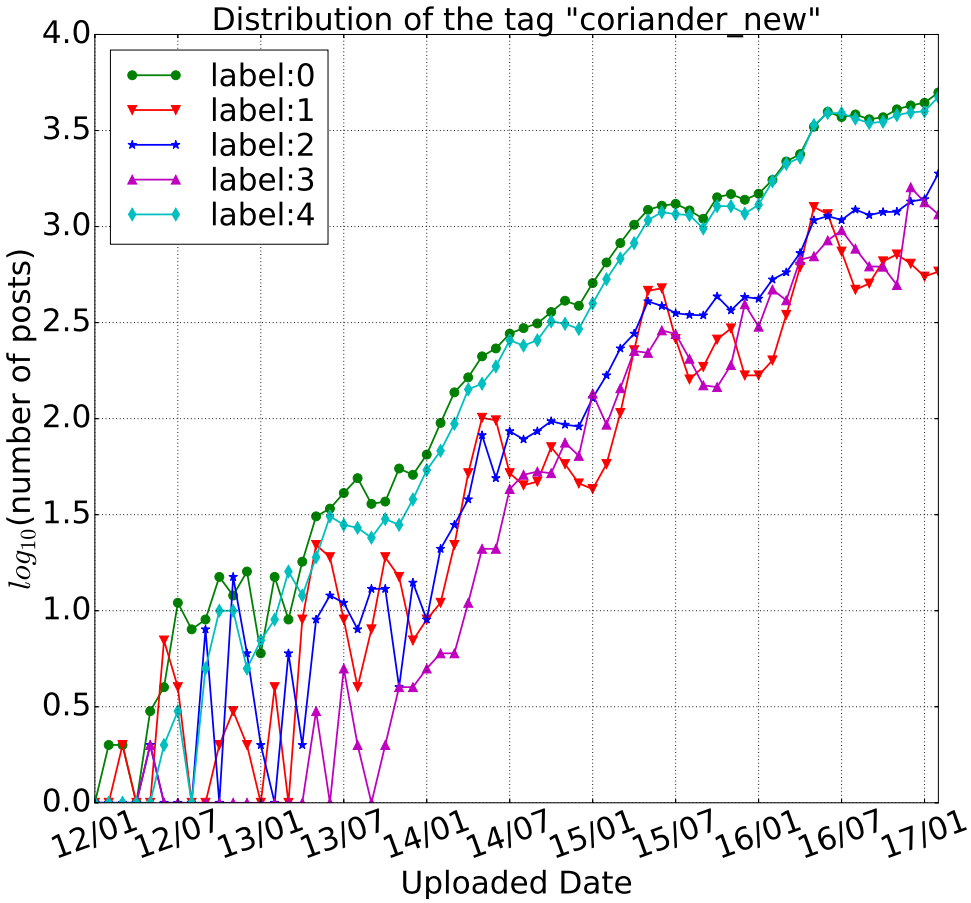


FIGURE 2.5 – Temporal evolution of the tag "coriander".

usually used in Asian cuisines as a spice. While recently, coriander specialty restaurant, coriander dessert and packaged foods such as coriander-flavored potato chips become a new trend between the young people in SNS.

Acai berry is known as one of the healthiest berries. Acai smoothie is delicious and easy to make, it becomes a popular cold drink in summer. From Figure 2.6, we can see that images tagged "acai" tend to increase in summer.

In Figure 2.7, we show the example of "pocky". As an example, "pocky" becomes highly trending in November each year nowadays. This is attributed to "Pocky and Pretz Day" observed by some marketing outlets on November 11. Due to the numbers "11 11" looking like four pocky sticks standing in a line. People will celebrate this day not only by eating pocky but also playing the pocky game, decorating pocky, building pocky towers and sharing images of pocky on social

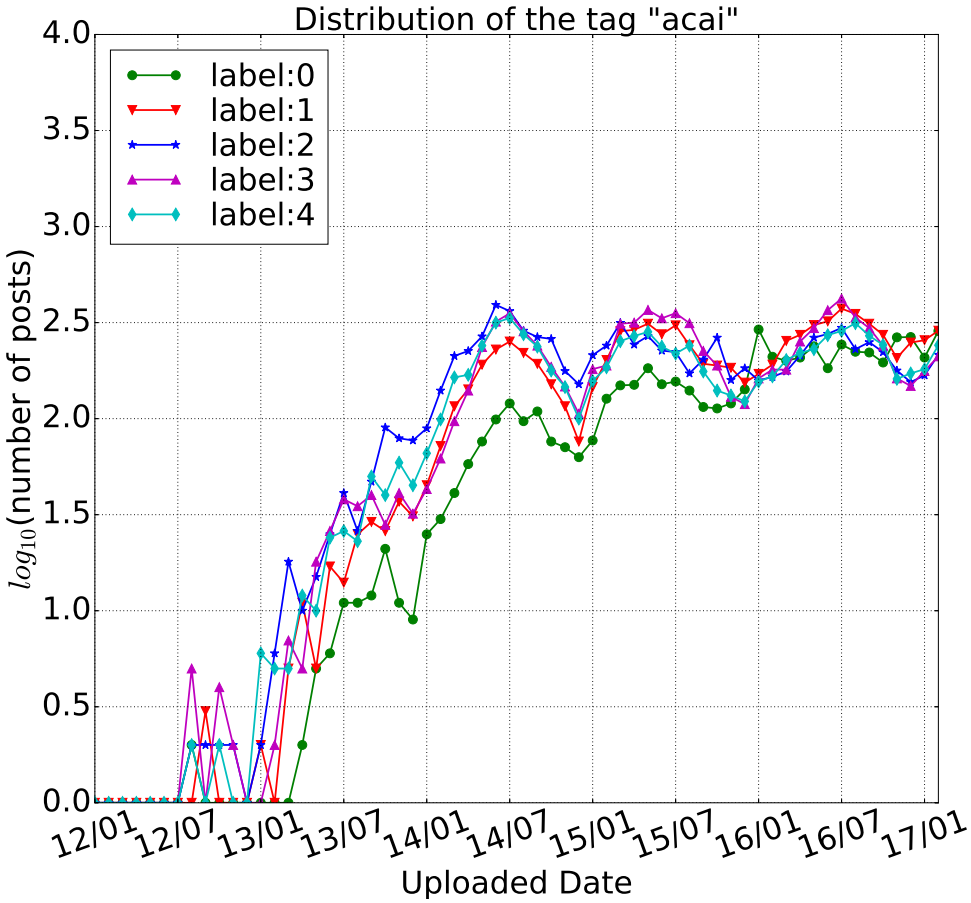


FIGURE 2.6 – Temporal evolution of the tag "acai".

media. Apart from an increased number of images in November, we also found that the number of images with label 0 and label 1 increased in February. We can attribute it to valentines day. Images with label 4 started peaking in August 2015, probably related to a Japanese music group called "Sandaime J Soul Brothers", a brand spokesman for pocky.

2.5. Conclusions

In this chapter, we focused on analyzing images and tags on Instagram. Since lots of images using the same tag may have completely different visual concepts, we applied image clustering in order to discover meaningful subsets of related images. After that, we analyzed and discussed temporal evolution of certain product-related tags.

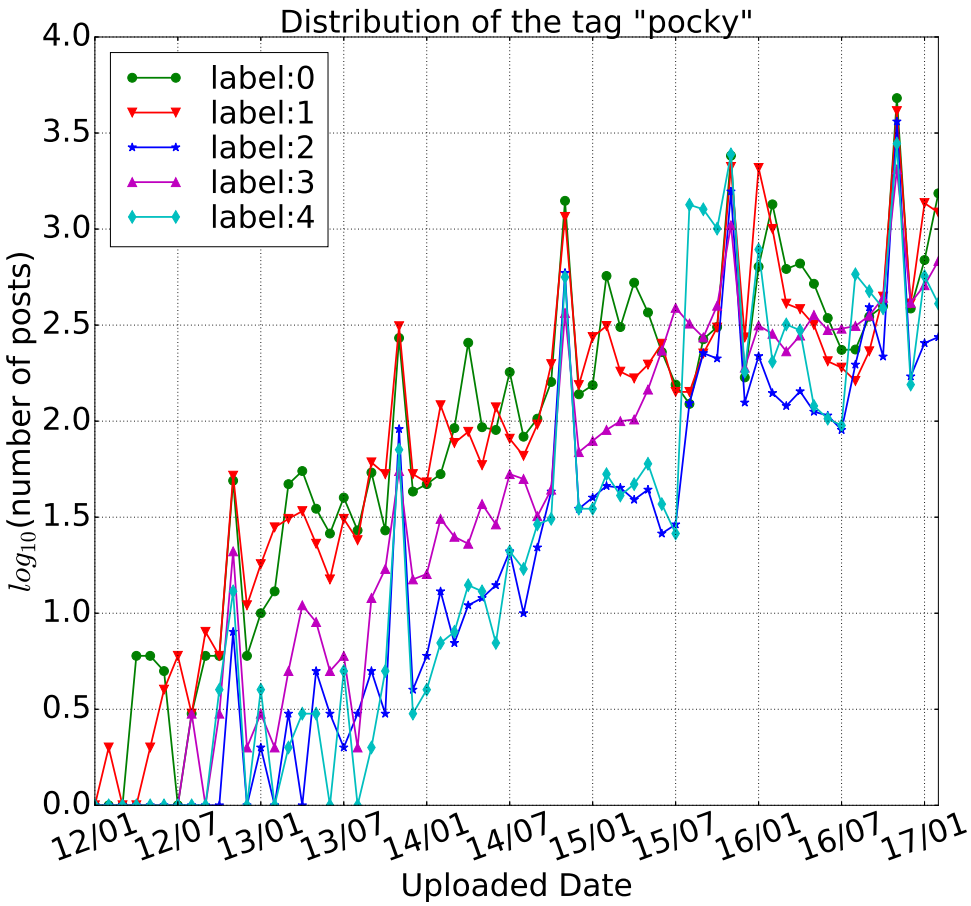


FIGURE 2.7 – Temporal evolution of the tag "pocky".

Chapter 3

Brands' Relationship Analysis

3.1. Introduction

In previous chapter, we used clustering to separate images into several meaningful subsets. We suppose that other objects such as brands, products and people can also be seperated too. In this chapter, we try separate brands by calculating similarity between them, and analyzing relationship between them.

Understanding relationship between brands, products and people has profound effect in marketing. In this chapter, we try to analyze brands' relationship using social media content, and we try to prove that users' preferences can be detected from social media. Understanding brands' relationship would provide great profits. We begin to think about capturing these kind of relationship between brands.

Co-purchasing history from credit card or point card in the shopping mall can be used to measure the similarity of brands. Unfortunately there are some demerits using it. Not all people own credit card, especially teenagers. Secondly, when the purchase amount is small, people prefer using cash. It results in low-price-range brands appearing in purchasing history seldomly. Many shopping malls have their own point card system, which allow customers to earn points every time they make a purchase from one of the franchises. Although point cards can record the purchase history, we are limited by how many brands are at the location of the purchase. Hence, the analysis is a bit limited by design. For these reasons, we chose social network data to measure the similarity between brands. Social media has no age or income requirement, also no limitations to number of brands being advertized by marketers or users. Other than measuring relationship between

FIGURE 3.1 – Example posts of using social media for marketing purpose.

brands, we think users' preferences detected from social media content can also be used to measure relationship between brands and people. We show two example posts of using social media for marketing purpose in Figure 3.1. Image in the left is posted by "MUJI" on Instagram. Image in the right is posted by "ORBIS" on Twitter.

Our goal is to find the relationship between brands. Instead of using posts by the brand itself, we assum followers of brands provide more clear representations of brands' relationship. One reason is that no matter what concept the brand has, customers' choices are more important in defining the relationship. Secondly, brands in the same category may have higher similarity. For example, a fashion brand will be closer to another fashion brand, than to a cosmetic brand. This is not what we seek. Finding the relationship between two diverse product categories is of more interest.

3.2. Related Works

More and more research nowadays is focusing on how online content are actually related to the real world. Many researches analyzed the popularity of brands and brands' posts. De Vries et al. identified that brand posts may be popular

due to several cues related to vividness, interactivity, informational content, entertaining content, position and valence of comments. They used regression models to find out which feature of social brand posts engage users [28]. Mazloom et al. focused on analyzing popularity of brand-related posts on Instagram. They identified that brand-related posts may be popular due to several cues related to factual information, sentiment, vividness and entertainment parameters about the brand [29]. Overgoor et al. combined spatial and temporal information to predict brand's popularity on Instagram [30].

Another group of researches focused on analyzing both consumers and brands. Goh et al. analyzed user-marketer interaction data from a fan page brand community on Facebook. They showed that engagement in social media brand communities leads to a positive increase in sales [31]. Laroche et al. showed that brand communities established on social media have positive effects on brand loyalty [32, 33]. The assumption of social media has positive effects on brands also proved in [34, 35, 36]. Dessart et al. analyzed factors that engage consumer in online brand communities. They identified three key engagement dimensions including cognition, affect and behaviours [37]. Hudson et al. explored how individual and national differences influence the relationship between social media and consumer-brand relationships [38].

In the study of relationship between music festival brand and visitor attendance, Lopez et al. confirmed that a balancing act is necessary with respect to brand popularity, similarity, and diversity and that being too unique as a festival brand can become a double-edged sword [39]. Tang et al. predicted users' retweet behavior by studying relationships between users and considering social similarity [40]. Cheung et al. analyzed relationship between users on Weibo using images uploaded by these users [41]. Bekk et al. also revealed this idea in the task of tour recommendation. They found that when people choose holiday destination, they considered both similarity and complementarity [42].

In the study of understanding brands' concept, Culotta et al. used data on Twitter to predict how consumers perceive brands' attributes including eco-friendliness, nutrition, and luxury [43]. Gelli et al. presented a study of image

recommendation to brands. They recommended users' images which are consistent to brand's stlye by learning features from images uploaded by these brands [44].

Previous works of measuring similarity between brands have been done by Bijmolt et al. [45]. They used questionnaires to ask people how close two products are in order to find out the similarity of brand's products. In this way, they were able to find the relationship between brands in different categories. But the limitation of this method is that it requires time and monetary investment in order to the gain enough data.

3.3. Dataset Construction

3.3.1. Data Collection

In the following part of this chapter, we present a new scale for measuring similarity between brands using social media content. We chose to collect posts from Instagram because many brands have created official accounts for the brand promotion purpose. We consider that those can be a valuable resource to analyze users' preferences on social media and customers' preferences in the real world.

We show the example of a fashion brand "SNIDEL" in Figure 3.2. "SNIDEL" is a female fashion brand which is popular among women in 20s. On the right side, we show a post example. It represents that most of them tend to use tags like **sweet** and **fashion** in their posts. This allows us to make quantitative comparisons between brands.

We selected 109 most popular Japanese company's official accounts. Here we define popularity as the number of followers the account has. We collected data on 109 brands via crawling these Instagram posts.

We randomly selected 1,000 users per brand and used their posts to represent this brand. We chose to associate a unique user to just one brand, finally the user dataset became 109,000 unique users. We show the example in Figure 3.3. Their posts represent what these users do in their daily life and we think these can be utilized to represent the similarity between brands.

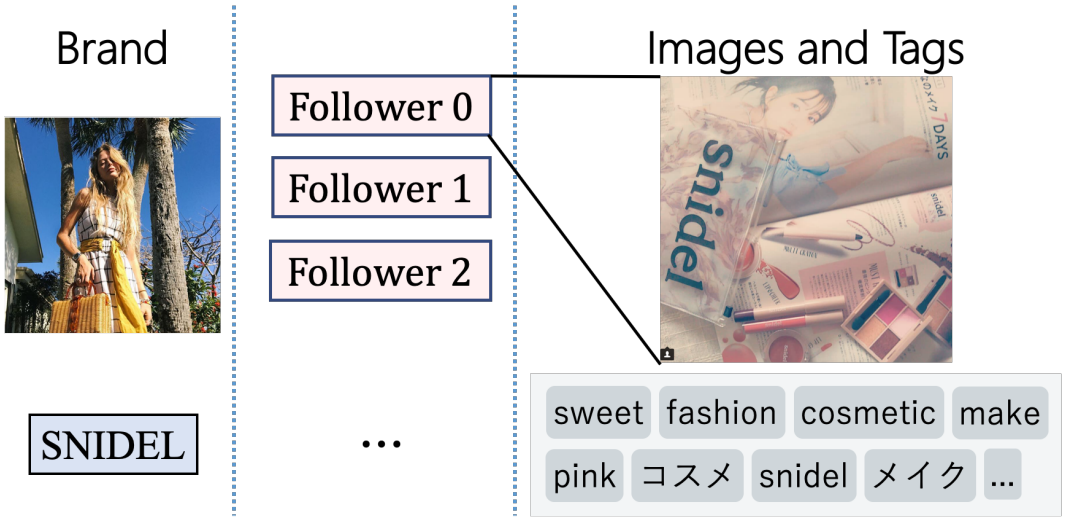


FIGURE 3.2 – The example of one fashion brand's followers' post.

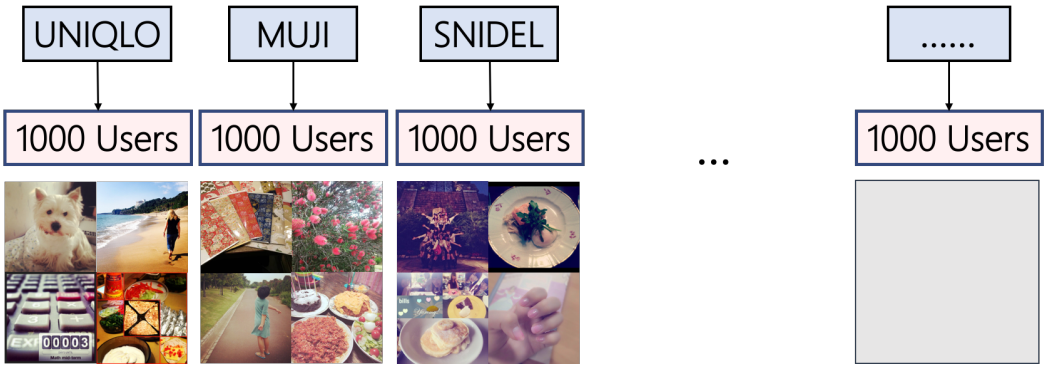


FIGURE 3.3 – Images uploaded by users who have favorited these brands.

3.3.2. Description of Datasets

In our following experiment, we create three datasets. We show the difference in Table 3.1. Popular109 dataset includes 109 most popular Japanese company's official accounts. We create two dataset Pointcard101 which includes 101 brands and Creditcard81 which includes 81 brands for evaluation purpose.

We obtained two customers' purchasing data. The first is customers' purchasing history from a shopping mall in Japan. The other one is customers' purchasing history from a credit card company in Japan. They are both anonymized before processing. Two datasets both include information about users buying specific brands. For the Pointcard101 dataset, we select 101 brands with more than 10,000 followers on Instagram for evaluation. For the Creditcard81 dataset, we select 81

Table 3.1 – Summary of dataset used in this thesis.

dataset	the number of brands	purchasing data	data source
Popular109	109	no	Instagram
Pointcard101	101	yes	point card in a certain mall
Creditcard81	81	yes	a certain national credit brand

brands with more than 5,000 followers on Instagram for evaluation. Then we collect data using the method we mentioned in previous section.

3.4. Proposed Methods

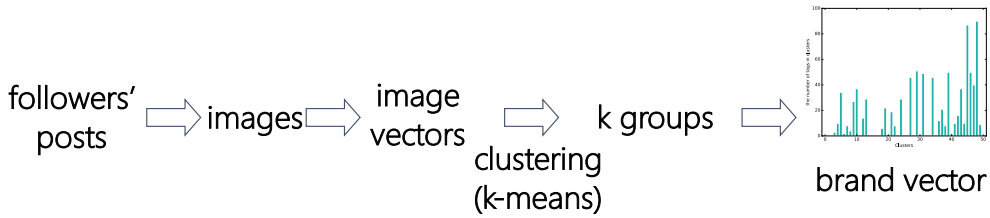
Existing measurement methods for analyzing similarity between brands only concentrate on the concept of the brand, or how close their products are. Other method like questionnaires costs a lot. Without enough samples, the result will be biased. Here, we present a new scale for measuring similarity between brands using content on social media by analyzing posts from brands' followers. In the following section, we introduce histogram based methods and tag selection based methods separately. Then we compare performance between them.

3.4.1. Histogram based Methods

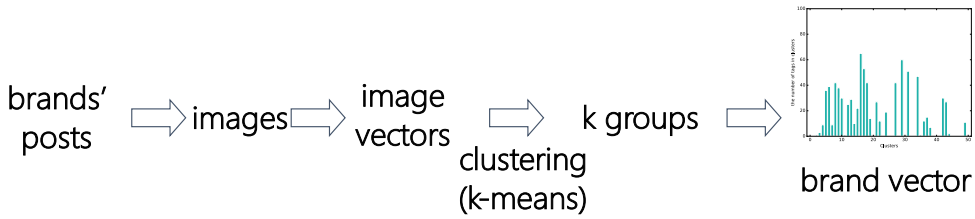
We show a flowchart of our proposed histogram based methods in Figure 3.4. In the following section, we introduce the details of how we analyze similarity between brands.

Image Feature

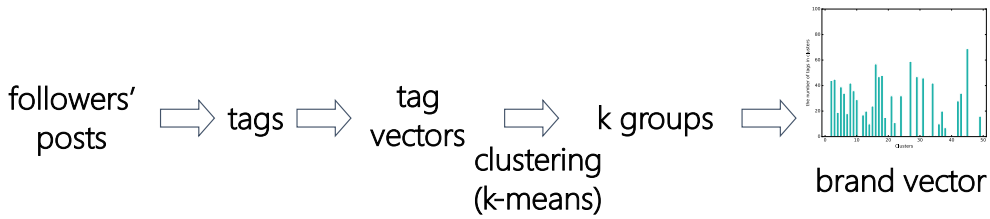
Since tremendous photographs were uploaded to social media everyday, it become a valuable data source for researchers. Analyzing photographs on social media has been a hot topic. Zhao et al. used geotagging images on social media for tour recommendation [46]. Segalin et al. used Facebook profile pictures to



(a) Followers' image feature.



(b) Brands' image feature.



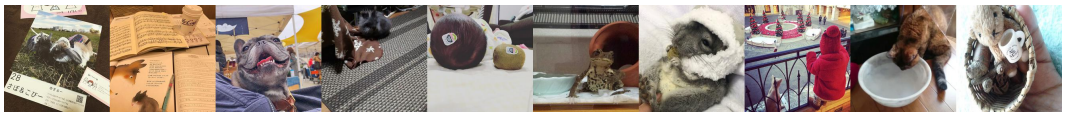
(c) Followers' tag feature.

FIGURE 3.4 – Flowcharts of proposed methods based on histogram.

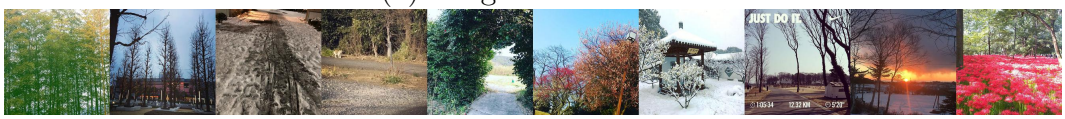
predict users' personality [47]. Many works have used images on social media for fashion understanding task [48, 49].

We also think photographs uploaded by users can represent their personality or preferences. In this section, we use photographs uploaded by users to analyze brands' similarity. For each brand, we use 10 most recent photographs from 1,000 users to represent it. We use a 50-layer ResNet [25] pretrained on ImageNet [26] to extract image features. Then, we use mini-batch K-means [27] to cluster features. Then we use K-means clustering with a setting of K = 50. Figure 3.5 shows the example of clustering results of images. Most observed images in cluster 0 are related to "animals", and in cluster 1 is representing "landscape". Most images in cluster 2 are related to nail manicure.

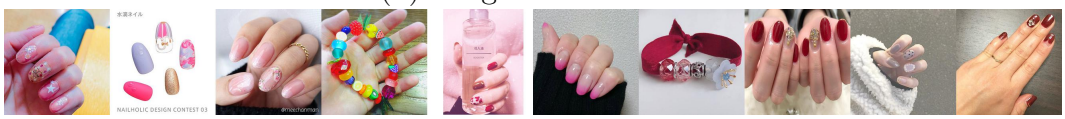
After clustering, we use the number of images in each cluster as the brand vector. In Figure 3.6(a), we show the number of images in each cluster for the brand "MUJI". Likewise, in Figure 3.6(b), we show the number of images in each



(a) images in cluster 0



(b) images in cluster 1



(c) images in cluster 2

FIGURE 3.5 – The result of image clustering.

cluster for the brand "UNIQLO". In the end, we calculate pearson correlation between each two brands as the similarity result.

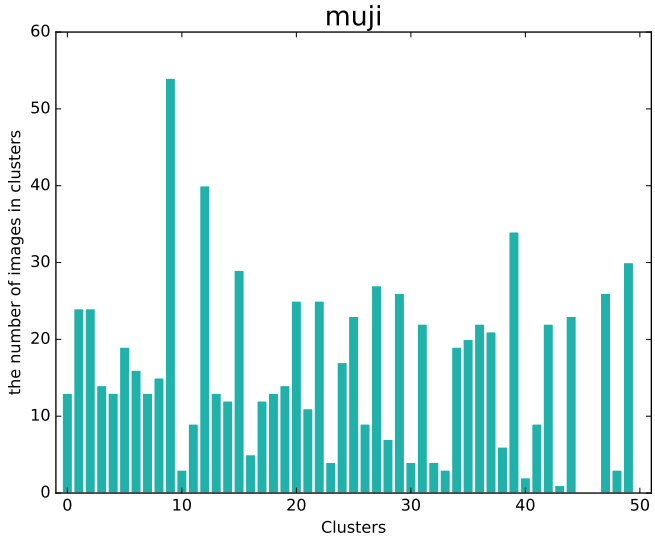
In the begining of the experiment, we also try the most direct way, using brand's post as the feature to analyze brand's similarity. We show two brands's posts in Figure 3.7 as the example. We can see that images from "MUJI" are most natural and mild. While images from "GRL" are full of warm colors.

We use the same procedure when we handle followers' images. We didn't use tag feature because some brands provide tags and title to the image, while some brands never use tags. And tags from the brand have little variety. It is hard to use text feature for similarity analysis. We compare the results by images from brands and images from followers in the evaluation.

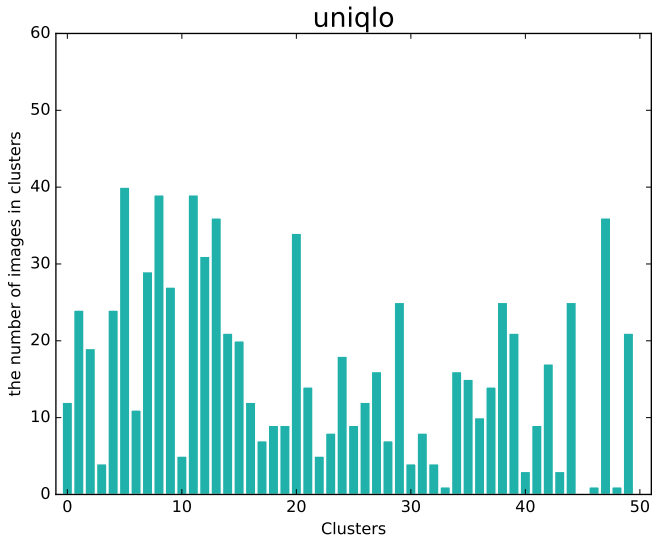
Followers' Tag Feature

In the work Item2Vec [50], they proposed a item-based Collaborative Filtering method that produces embedding for items in a latent space. They considered items purchased by one user as a positive example, then used skip-gram model in Word2Vec [51] to embedding them. Eisner et al. used similar method to convert emoji to vector [52].

We use the data collected above to train the Tag2Vec. We consider an image and tags belonging to it as a positive example. Then use *fasttext* [53] to convert each tag to a 100 dimension vector.



(a) the brand "MUJI"



(b) the brand "UNIQLO"

FIGURE 3.6 – The number of images in each cluster.

We rank tags by the number of users who have used the tag at least once. For each brand, we use 3000 most frequently used tags to represent it.

After embedding, we use mini-batch K-means [27] to cluster them. We use K = 50 as an example to show our results. In Table 3.2 and Table 3.2, we show clustering results of tags after using Tag2Vec. We can see that most tags in cluster 22 are related to "photography" or "travelling", and most tags in cluster 47 are related to "fashion".

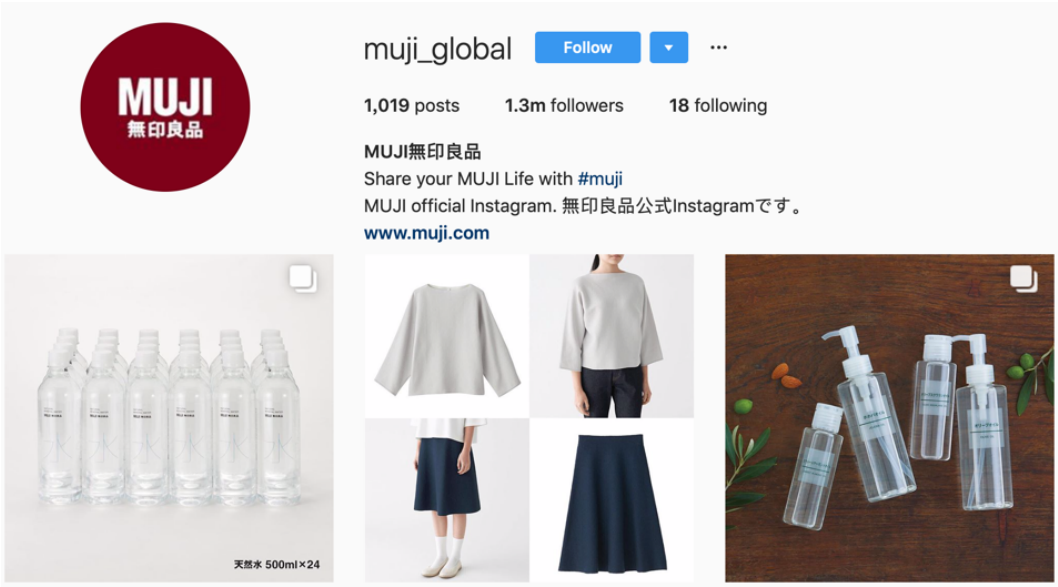
TABLE 3.2 – The result of tag clustering.

(a) tags in cluster 22

photography	travel	nature	photooftheday
picoftheday	sunset	vsco	photographer
vscocam	igers	instatravel	travelgram
street	italy	architecture	blackandwhite
travelphotography	photoshoot	view	bestoftheday
streetphotography	wanderlust	city	traveling

(b) tags in cluster 47

fashion	ootd	お洒落さんと繋がりたい (want to connect with fashionable people)	ファッション (fashion)
おしゃれさんと繋がりたい (want to connect with fashionable people)	instafashion	outfit	今日のコーデ (today's coordination)
コーデ (coordinate)	コーディネート (coordinate)	プチプラ (affordable)	coordinate
おしゃれ (fashionable)	code	ママコーデ (coordination for mother)	プチプラコーデ (stylish but affordable coordination)
お洒落 (fashionable)	オシャレ (fashionable)	今日の服 (today's outfit)	nike
gu	シンプルコーデ (simply coordination)	大人カジュアル (mature casual)	お気に入り (favorite)

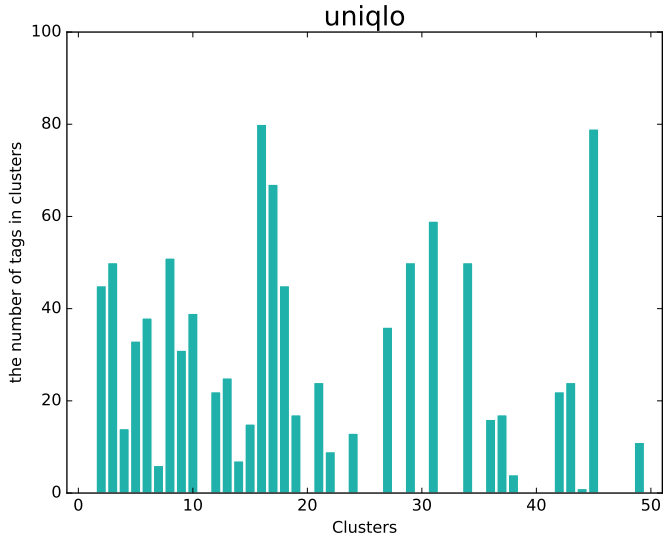


(a) Images from "MUJI".

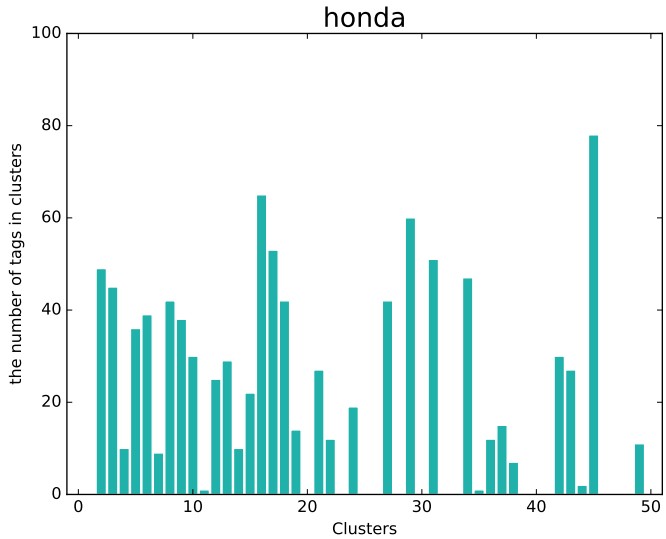
(b) Images from "GRL".

FIGURE 3.7 – Example of images posted by "MUJI" and "GRL".

In Figure 3.8(a), we show the number of tags in each cluster for the brand "UNIQLO". In Figure 3.8(b), we show the number of tags in each cluster for the brand "Honda". After clustering, we use the number of tags in each cluster as the brand vector. In the end, we calculate pearson correlation between each two brands as the similarity result.



(a) the brand "UNIQLO"



(b) the brand "Honda"

FIGURE 3.8 – The number of tags in each cluster.

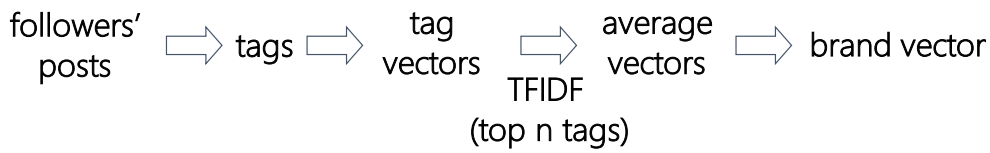
3.4.2. Tag Selection based Methods

Different from histogram based methods, we focus on selecting important tags here. We show the flowchart of our proposed methods in Figure 3.9.

Rank by User Frequency

In this method, we select top 3000 tags to represent the brand. For tag ranking, we rank tags by the number of users who have used the tag at least once. In other

(a) Rank by User Frequency.



(b) Rank by TF-IDF Score.

FIGURE 3.9 – Flowcharts of proposed methods based on tag selection.

words, no matter how many times the user has used the tag "instagood", we only count once for one user. In [54], they observed that lots of users apply same tags to every photo. Using the brand "Starbucks" and "MUJI" as the example, Table 3.3 shows the tags that appear in most photos. Table 3.4 shows the tags that have been used by the most users. From these tables, we can see that using the number of users who have used the tag at least once are more relevant.

Rank by Tag Score

In this method, the difference with the previous method is in the tag ranking process. Instead of using the number of users who have used the tag at least once, we apply TF-IDF [55] when selecting tags. TF-IDF is a numerical statistic that is intended to reflect how important a word is to a document in a collection or corpus [56]. TF reflects how often the word is used and IDF corresponds to the rareness of the word across all documents.

TF-IDF score is calculated using following:

$$tf\_idf(t_i, d_j) = tf(i,j) \times idf(i), \tag{3.1}$$

$$tf(i,j) = \sum_k \frac{n_{i,j}}{n_{k,j}}, \tag{3.2}$$

$$idf(i) = \log \frac{D}{m_i} + 1, \tag{3.3}$$

where $n_{i,j}$ is the frequency that the word t_i appeared in document d_j, D is the number of documents, m_i is the number of documents that including the word t_i. From this representation, we can know that the TF-IDF score would be high if the word appeared in d_j frequently. And if the word had been used in many documents, its' score would be lower.

In the task of fashion style prediction, Hsiao et al. used topic model to predict fashion style [57, 58]. They consider a description as a document, words inside a description as words inside a document. In our tag selection algorithm, we consider a brand as a document, and tags inside a brand as words inside a document. We use the number of users who have used the tag at least once to represent TF. If more people have used the tag, the score would be higher. For the IDF part, we consider that if the tag has been used in other brands frequently, its' score would be lower. Since lots of tags have appeared in every brand, it might result in that most tags' IDF score is 1. We set the tag frequency at top of the ranking, it would be counted the tag appeared in other brands. Tag's score is calculated using following equation:

$$tag\_score(t_i, b_j) = tf(i,j) \times idf(i), \tag{3.4}$$

$$tf(i,j) = \sum_k \frac{n_{i,j}}{n_{k,j}}, \tag{3.5}$$

$$idf(i) = \log \frac{B}{\sum_j c_{i,j}} + 1, \tag{3.6}$$

where $n_{i,j}$ is the number of users have used tag t_i in brand b_j, B is the number of brands. $c_{i,j}$ is 1 if the tag t_i appeared in brand b_j's top n tags, else $c_{i,j}$ is 0. We set $n = 1000$ in this experiment.

We select top 3000 tags then average tag vectors and use this vector as brand vector. We also try multiply tag vector with tag score, then average vectors and use this vector as brand vector.

We also use two brands, "Starbucks" and "MUJI" as the example. In Table 3.4, we show top 20 tags of rank by TF-IDF score.

Table 3.3 – Compare top 20 tags rank by tag frequency in "Starbucks" and "MUJI".

Starbucks	MUJI
instagood	art
love	instagood
l4l	japan
いいね返し (like for like)	design
スタバ (starbucks)	photography
japan	fashion
starbucks	travel
写真好きな人と繋がりたい (I want to connect with people who like photographs)	architecture
happy	tokyo
カフェ (cafe)	love
カメラ女子 (camera girls)	photooftheday
ネイル (nail)	coffee
桜 (cherry blossom)	photo
instagram	daily
ランチ (lunch)	food
ねこ (cat)	drawing
スイーツ (sweets)	dog
カフェ巡り (cafe-hop)	illustration
cute	nature
photography	vsco

Table 3.4 – Compare top 20 tags rank by user frequency in "Starbucks" and "MUJI".

Starbucks	MUJI
スタバ (starbucks)	art
桜 (cherry blossom)	coffee
ありがとう (thank you)	桜 (cherry blossom)
starbucks	love
ランチ (lunch)	japan
カフェ (cafe)	flowers
かわいい (cute)	2018
love	spring
instagood	travel
楽しかった (I had a good time)	cafe
誕生日 (birthday)	sky
可愛い (cute)	sunset
スターバックス (starbucks)	photography
クリスマス (christmas)	design
美味しい (delicious)	tokyo
海 (sea)	lunch
いちご (strawberry)	nofilter
cafe	nature
パンケーキ (pancake)	happy
大好き (very fond of)	blue

Table 3.5 – Compare top 20 tags rank by TF-IDF score in "Starbucks" and "MUJI".

Starbucks	MUJI
ストロベリーベリーマッチフラペチーノ (strawberry verymuch frappuccino)	studygram
キャラメルマキアート (caramel macchiato)	calligraphy
STARBUCKS	bamboo
感動した (I was moved)	architecture
夜食 (midnight snack)	lamp
スタバ好き (I love starbucks)	oldtown
ピーチ (peach)	tulips
おなかいっぱい (I'm full)	lettering
ピーチピンクフルーツフラペチーノ (peach pink fruits frappuccino)	furniture
スタバカード (starbucks' card)	봄 (spring)
頑張ろ (work hard)	inspiration
抹茶クリームフラペチーノ (green tea frappuccino blended creme)	sign
玉子焼き (omelet)	crafts
札幌ドーム (sapporo dome)	window
アプリ (apps)	lighting
失敗 (fail)	kitchen
strawberryverymuchfrappuccino	homedecor
Starbucks	sketch
頑張った (worked hard)	typography
楽しかった (I had a good time)	interiors

FIGURE 3.10 – Two brands with the highest similarity based on followers' image features.

3.4.3. Experiment Results and Visualization

After calculating Pearson correlation between each pair of brands, we can rank these pairs according to Pearson correlation coefficient. We use dataset Popular109's result as the example here.

In histogram based methods, two brands with highest similarity based on followers' image features are "EVRIS" and "SLY". We show posts from these two brands's official accounts in Figure 3.10. Four posts on the left side are from "EVRIS" and four posts on the right side are from "SLY". We can see that they are both in "cool fashion" category.

Based on brands' image features, two brands with highest similarity are "AZUL BY MOUSSY" and "MOUSSY". Likewise, we show posts from these two brands's official accounts in Figure 3.11. We can see that they are both in casual style.

Two brands with the highest similarity based on tag features are "GRL" and "NICE CLAUP". We show posts from these two brands's official accounts in Figure 3.12. We can see that they are both in "sweet fashion" category.

FIGURE 3.11 – Two brands with the highest similarity based on brands' image features.

FIGURE 3.12 – Two brands with the highest similarity based on followers' tag features.

In Popular109 dataset, we have 109 brands. In the similarity calculation process, we have 5886 unique ranking pairs. In histogram based methods, the Spearman ranking correlation coefficient is 0.73 between tag features based and image features based. We show the visualization of the similarity between brands based on histogram method using tag feature in Popular109 dataset in Figure 3.13. On

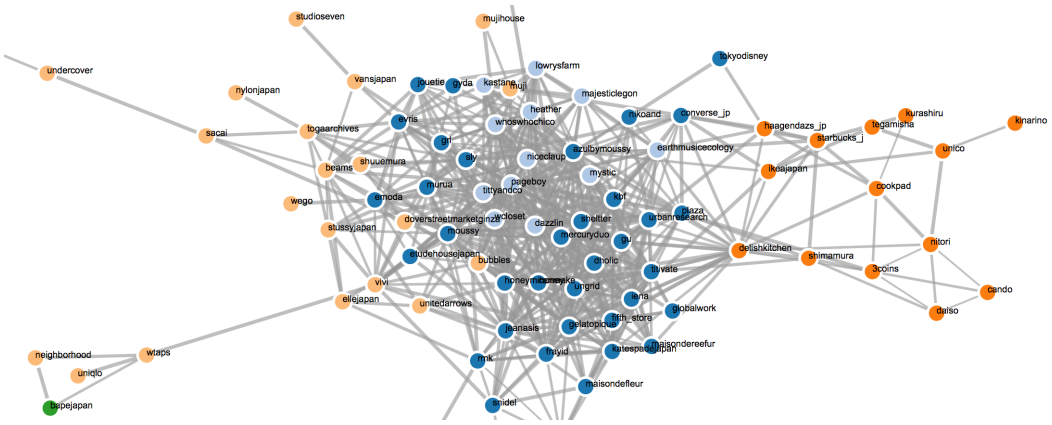


FIGURE 3.13 – Visualization of brands' relationship in Popular109 dataset.

the right side of the figure, we can see that 100 yen and 300 yen store like "Daiso", "CAN DO" and "3COINS" are very closed to each other.

We show some examples using tag selection based methods in Popular109 dataset. In Table 3.6, we show images from "who's who Chico" and "PAGEBOY". And we show top 20 tags ranking by user frequency. "who's who Chico" and "PAGEBOY" are female fashion brands, their clothes are both casual and vintage. In Table 3.7, we show images from "Cookpad" and "titivate". And we show top 20 tags ranking by user frequency. "Cookpad" is a recipe sharing platform. It is Japan's largest recipe sharing service. "titivate" is a female fashion brand, which style is elegant.

In Table 3.8, we show images from "Starbucks" and "earth music&ecology". And we show top 20 tags ranking by TF-IDF score from their followers. "Starbucks" is an American coffee company and coffeehouse chain. "earth music&ecology" is a female fashion brand, which style is natural and comfortable. In Table 3.9, we show images from "gelato pique" and "SNIDEL". And we show top 20 tags ranking by TF-IDF score from their followers. "gelato pique" is a sleepwear brand. "SNIDEL" is a female fashion brand, which style combines street culture and elegance. These two brands belong to the same company "MASH Style Lab Co.,Ltd.".

TABLE 3.6 – High similarity brands in Popular109 dataset based on tag feature (rank by user frequency).

(a) Images by who's who Chico

(b) Images by PAGEBOY

Top 20 tags ranking by user frequency.

who's who Chico	PAGEBOY
instagood	instagood
cafe	love
love	cafe
disney	ありがとう (thank you)
pink	桜 (cherry blossoms)
ありがとう (thank you)	ootd
l4l	l4l
disneysea	disney
プリント倶楽部 (print club)	pink
cute	happybirthday
lunch	disneysea
桜 (cherry blossoms)	starbucks
ootd	cute
happybirthday	lunch
京都 (kyoo)	プリント倶楽部 (print club)
flower	fashion
instafood	カフェ (cafe)
disneyland	京都 (kyoto)
カフェ (cafe)	bff
ディズニー (disney)	2018

TABLE 3.7 – High similarity brands in Popular109 dataset based on tag feature (rank by user frequency).

(a) Images by Cookpad

(b) Images by titivate

Top 20 tags ranking by user frequency.

Cookpad	titivate
桜 (cherry blossoms)	桜 (cherry blossoms)
ランチ (lunch)	ありがとう (thank you)
ありがとう (thank you)	ランチ (lunch)
love	cafe
instagood	カフェ (cafe)
lunch	lunch
japan	クリスマス (christmas)
海 (sea)	誕生日 (birthday)
ケーキ (cake)	京都 (kyoto)
food	海 (sea)
手作り (handmade)	love
カフェ (cafe)	お花見 (cherry-blossom viewing)
誕生日 (birthday)	かわいい (cute)
happy	幸せ (happiness)
美味しい (delicious)	スタバ (starbucks)
可愛い (cute)	大阪 (osaka)
クリスマス (christmas)	happybirthday
cafe	結婚式 (wedding)
スタバ (starbucks)	プレゼント (present)
いちご (strawberry)	おめでとう (congrats)

TABLE 3.8 – High similarity brands in Popular109 dataset based on tag feature (rank by TF-IDF score).

(a) Images by Starbucks

(b) Images by earth music&ecology

Top 20 tags ranking by TF-IDF score.

Starbucks	earth music&ecology
ストロベリーベリーマッチフラペチーノ (strawberry verymuch frappuccino)	earthmusicandecology
キャラメルマキアート (caramel macchiato)	プリント倶楽部 (print club)
STARBUCKS	笑った (laughed)
感動した (I was moved)	tullyscoffee
夜食 (midnight snack)	でぶ活 (to eat a lot to be fat)
スタバ好き (I love starbucks)	広瀬すず (suzu hirose)
ピーチ (peach)	たくさん (many)
おなかいっぱい (I'm full)	ケンタッキー (kentucky)
ピーチピンクフルーツフラペチーノ (peach pink fruits frappuccino)	おつかれ (good job)
スタバカード (starbucks' card)	ほろよい (tipsy)
頑張ろ (work hard)	春水堂 (chun shui tang)
抹茶クリームフラペチーノ (green tea frappuccino blended creme)	テスト勉強 (study for exam)
玉子焼き (omelet)	😊
札幌ドーム (sapporo dome)	ちはやふる (chihayafuru)
アプリ (apps)	いっぱい (many)
失敗 (fail)	ぷりんと倶楽部 (print club)
strawberryverymuchfrappuccino	大好きな (favorite)
Starbucks	0505
頑張った (worked hard)	シロノワール (shiro-noir)
楽しかった (I had a good time)	最高でした (it was awesome)

TABLE 3.9 – High similarity brands in Popular109 dataset based on tag feature (rank by TF-IDF score).

(a) Images by gelato pique

(b) Images by SNIDEL

Top 20 tags ranking by TF-IDF score.

gelato pique	SNIDEL
gelatopique	snidel
ジェラートピ (gelatopique)	salon
tiffany	サロモ (salon model)
ジェラピケ (gelatopique)	カチューシャ (hair band)
ルームウェア (room wear)	hairsalon
snsd	セルフィー (selfie)
ひたち海浜公園 (hitachi seaside park)	プリント倶楽部 (print club)
明治神宮 (meiji shrine)	サロン (salon)
snidel	ミディアム (medium)
愛知 (aichi)	旅館 (hostel)
ハートネイル (heart nail)	二日酔い (hangover)
exo	🌼
ショートネイル (short nail)	東京観光 (tourism in tokyo)
missdior	ゆるふわ (soft and fluffy)
다이어트 (diet)	roomwear
サンシャイン水族館 (sunshine aquarium)	代官山カフェ (daikanyama cafe)
꽃 (flower)	三宮 (sannomiya)
벚꽃 (cherry blossom)	ファッションショー (fashion show)
popupshop	撮影モデル (shooting model)
バレンタインネイル (valentine's day nail)	最強 (almighty)

3.5. Evaluation

3.5.1. Stability

Since our proposed methods are based on randomly selected 1,000 users per brand, we conducted experiment to evaluate the stability of our proposed methods. For each brand, we randomly split 1,000 users into two groups, then computed similarity between brands based on each group. We compared similarity results computed based on two groups using spearman ranking correlation coefficient. We randomly split dataset for 5 times, and the average Spearman ranking correlation coefficient is 0.98. It proves that our proposed methods are very stable.

3.5.2. Evaluation using Co-Purchasing Data

In order to prove that our results have correlation with real-world business. We compared our results with customers' purchasing history from dataset Point-card101 and Creditcard81.

Based on co-purchasing data, we were able to create brand-user matrix:

$$M_{b_i u_j} = t, \tag{3.7}$$

which means user u_j bought brand b_i for t times.

Then, we calculated Pearson correlation coefficient between each pair of brands. For example, Pearson correlation between brand b_i and brand b_k are calculated as follow:

$$\rho = \frac{\mathrm{cov}(M_{b_i}, M_{b_k})}{\sigma_{M_{b_i}} \sigma_{M_{b_k}}}, \tag{3.8}$$

where M_{b_i} represents brand b_i's vector and M_{b_k} represents brand b_k's vector.

For our proposed methods, we collected data and calculated Pearson correlation coefficient between each pair of brands take the same procedure as in previous chapter. Then we compared our results with co-purchasing result.

3.5.3. Evaluation using Questionnaires

In order to further evaluate our results, we took questionnaires by asking whether they have purchased certain brands before. Since our co-purchasing data only included Japanese customers, we did our questionnaires on Yahoo! crowdsourcing [59].

Since most brands in the dataset Pointcard101 and Creditcard81 are female fashion brands, we allowed female to answer the question. We conducted two questionnaires separately for dataset Pointcard101 and dataset Creditcard81. In the first questionnaires, 900 people participated in our task. In the second questionnaires, 890 people participated in our task. We selected famous brands to ensure that people had bought them at least once. We selected top 50 brands from the dataset according to the number of followers on Instagram. The format of two questionnaires was similar. For each brand, we ask people three questions.

- Have you purchased this brand by yourself before?
- Are you interest in this brand?
- Do you know this brand?

We show the interface of our questionnaires in the Figure 3.14.

We set some attention checks in order to ensure the quality of results. We also delete the user who answer they have bought the brand but don't know them. In the end, the first questionnaires includes 804 people and the second questionnaires includes 775 people.

From the questionnaires, we obtained users' co-purchasing and interest tendencies. Similar to purchasing data in previous section, we created three brand-user matrix which represent co-purchasing result, interest tendency and reputation result separately. For example, for the question "Have you purchased this brand by yourself before?", $M_{b_i u_j} = 1$ means user u_j has bought brand b_i before, and $M_{b_i u_j} = 0$ means means user u_j has not bought brand b_i before. Then, we calculated Pearson correlation coefficient between each pair of brands.

FIGURE 3.14 – The interface of our questionnaries.

3.6. Results and Discussion

In the Table 3.10, we show Spearman ranking correlation coefficient between brand similarity based on our proposed methods and brand similarity based on point card and credit card's co-purchasing results. We can see that tag feature works better than image feature when comparing with co-purchasing result. Tag selection based methods work better than histogram based methods.

Table 3.10 – Spearman ranking correlation coefficient beween proposed methods and co-purchasing result.

	co-purchasing data	
feature	Pointcard101	Creditcard81
image-histogram (brand)	0.10	0.21
image-histogram (follower)	0.33	0.34
tag-histogram	0.42	0.41
tag-frequency	0.43	0.42
tag-user-frequency	0.44	0.43
tag-tfidf	**0.45**	**0.44**
tag-tfidf-weight	0.43	0.43

We also compared our proposed methods with questionnaires. In the Table 3.11, we can see that when compared with questionnaires' co-purchasing result, point card's co-purchasing result has higher Spearman ranking correlation coefficient. But when compared with questionnaires' interest and known result, proposed method base on tag selection has higher Spearman ranking correlation coefficient.

Table 3.12 shows results in credit card dataset. When compared with questionnaires co-purchasing, interest and known results, proposed methods using tags show stronger correlation than credit card's co-purchasing results.

From these results, it can be said that we have grasped the tendency of customers' preferences. Our proposed methods can predict customers' interest more accurately than predict customers' purchasing history. We assumed that our proposed methods could be related to customers' purchasing plan in the future.

TABLE 3.11 – Spearman ranking correlation coefficient beween proposed methods and questionnaires in Pointcard101 dataset.

	questionnaires		
feature	buy	interest	know
image-histogram	0.25	0.34	0.28
tag-histogram	0.34	0.47	0.46
tag-frequency	0.33	0.50	0.48
tag-user-frequency	0.32	**0.51**	**0.49**
tag-tfidf	0.34	0.50	0.48
tag-tfidf-weight	0.33	0.50	0.48
co-purchasing result (Pointcard101)	**0.52**	0.23	0.21

TABLE 3.12 – Spearman ranking correlation coefficient beween proposed methods and questionnaires in Creditcard81 dataset.

	questionnaires		
feature	buy	interest	know
image-histogram	0.20	0.30	0.15
tag-histogram	**0.32**	0.40	**0.26**
tag-frequency	0.30	0.37	0.23
tag-user-frequency	0.30	0.39	0.22
tag-tfidf	0.31	**0.41**	0.22
tag-tfidf-weight	0.31	**0.41**	0.23
co-purchasing result (Creditcard81)	0.28	0.33	0.17

3.7. Conclusions

In this chapter, we proposed a new scale for measuring the similarity between brands, using tag feature and image feature from their followers' posts. Then we took questionnaires via Yahoo! crowdsourcing in order to further evaluate our proposed methods. In the end, we evaluated our results by comparing with both the real-world customers' co-purchasing history and questionnaires. As a result, we found that our proposed methods have moderate correlation with customers' co-purchasing history. And for questionnaires, we found that our proposed methods' results show stronger correlation with people's interest than results using customers' co-purchasing history.

Chapter 4

Conclusions and Future Works

4.1. Conclusions

In this thesis, we presented a study of users' preferences understanding using social media content.

We begin with the introduction of social media and how it bring a new marketing approach social media marketing.

Then we analyzed posts related to products or services on Instagram. When analyzing product's popularity through tags, we found several images using the same tag but having completely different visual context. We applied image clustering in order to discover meaningful subsets of related images. After that, we analyzed and disscussed temporal evolution of certain products's popularity.

After that, we proposed a new scale for measuring the similarity between brands, using tag feature and image feature from their followers' posts. Then we evaluated our results by comparing with both the real-world customers' co-purchasing history and questionnaires. As a result, we found that our proposed methods have moderate correlation with customers' co-purchasing history. And for questionnaires, we found that our proposed methods' results show stronger correlation with people's interest than results using customers' co-purchasing history. It proved our assumption in the begining of this paper that we could grasp the tendency of customers' preferences using social media content.

4.2. Future Works

In the future work, we would like to use this method to measure the similarity between users, products or locations. Understanding relationship between users and products can help brands to find suitable celebrities for endorsements. Understanding relationship between users and locations is important in the task tour recommendation. In addition, we would like to analyze the style of images posted by these brands. We would like to further analyze that for brand-related posts, how the style of the image would affect its popularity.

Appendix A

Tag Recommendation based on Computer Vision and FPRank

A.1. Introduction

Social networking services (SNS) have become an important part of people's daily life. Most image sharing services such as Flickr and Instagram, they allow users to add tags to their images. Adding popular tags will help other people find the image easily, tags are an important part of images' popularity [60]. Since search engine is the main way to retrieve other people's image, adding important tags would help user gain higher popularity. Also, tags have become important user-defined data and are easy to analyze and computationally efficient, compared to complicated social connections or computationally costly visual features.

But tagging is a time-consuming process, and most people don't know what kind of tag they should add. So our aim is to design a recommendation system which can help users add tags that can contribute to popularity enhancement.

A.2. Related Works

A.2.1. Social Popularity Prediction

Predicting how much popularity the content would get is an important research topic [61]. Nowadays, generating online content has become popular since it is very easy and costless, resulting in a world saturated with information. Predicting popularity of online content has profound impacts, since it offers useful information and business opportunities. Accurate popularity prediction can help improve user experience, service effectiveness, and it has wide range of application areas such as content recommendation, network dimensioning, online advertising and information retrieval.

A.2.2. Tag Recommendation

Tag recommendation and refinement in social network help users to annotate more tags with less effort, and to consolidate vocabulary across users. There are many works focused on collaborative filtering (CF for short) based methods [62, 63, 64]. Because it is the most prominent and frequently used recommendation

techniques. While CF based methods do not consider popularity effect. Yamasaki et al. have proposed Folk Popularity Rank (FPRank for short) [65] aiming to help users to boost the popularity. The algorithm is inspired by the PageRank [66] and FolkRank [67].

But previous work could only recommend tags when images have original tags already. In this work, we using computer vision technology to add tags to original images automatically, then recommend tags to it based on FPRank algorithm. Also, we design a recommendation system which can help users add tags that can contribute to popularity enhancement.

A.3. FPRank Algorithm

The main idea of FPRank consists of two assumptions: (1) tags used for popular content are important, (2) the tags co-occurring with such important tags are also important. In contrast to FolkRank, we only consider the relation between content and tags.

The FolkPopularityRank score, $\mathbf{s}$, is computed as follows:

$$\mathbf{r}^1 = d\widetilde{\mathbf{A}}_{pop}\mathbf{r}^1 + (1-d)\mathbf{p}, \tag{A.1}$$

$$\mathbf{r}^0 = d\widetilde{\mathbf{A}}_{tag}\mathbf{r}^0 + (1-d)\mathbf{p}, \tag{A.2}$$

$$\mathbf{s} = \mathbf{r}^1 - \mathbf{r}^0, \tag{A.3}$$

where $\mathbf{r}$ is a weight vector with one entry for each tag, $\mathbf{r}^0$ is the tag-only FolkRank score, $d \in (0,1)$ is a damping factor and $\mathbf{p}$ is a random surfer component. $\widetilde{\mathbf{A}}_{pop}$ is a column stochastic matrix of the $\mid T \mid \times \mid T \mid$ adjacency matrix $\mathbf{A}_{pop}$, and so is $\widetilde{\mathbf{A}}_{tag}$ of $\mathbf{A}_{tag}$. The entries of $\mathbf{A}_{pop}$ and $\mathbf{A}_{tag}$, represented as $a_{i,j}$ and $a'_{i,j}$ respectively, are defined as

$$a_{i,j} = \sum_{t_i,t_j \in c_k} \frac{Popularity\,(c_k)+1}{number\ of\ tags\,(c_k)}, \tag{A.4}$$

$$a'_{i,j} = \sum_{t_i,t_j \in c_k} \frac{1}{number\ of\ tags\,(c_k)}, \tag{A.5}$$

TABLE A.1 – Overview of training and test sets.

Dataset	Average Views	Number of Images
Training Set	13,139.5	60,000
Flickr Popular Set	14369.2	1,000
Flickr Common Set	221.4	1,000
MCS Set	-	1,000

In addition, $d \in (0, 1)$ is a damping factor and $\mathbf{p}$ is a random surfer component.

Tags can be recommended by the following equation,

$$\mathbf{w}_{FP} = \mathbf{s}^{(d=1)} - \mathbf{s}^{(d=0)}, \tag{A.6}$$

where $\mathbf{w}_{FP}$ is a weight vector with one entry for each tag. For recommendation, the random surfer component for the already existing tags is set to 1, and the others are set to $0 \sim 1$; the eq. (1) is iterated until convergence. Setting the random surfer component p in this manner causes tags co-occurring with the already existing tags to be extracted. In addition, tag scores are redistributed by the content's popularity. The final tag scores correspond to the influence of the tags' popularity scores.

A.4. Datasets

The training were performed on the Yahoo Flickr Creative Commons 100M (YFCC100M) dataset [68]. We randomly selected 60,000 images that have more than 20 tags and over 5000 views from the YFCC100M for training. We have created three datasets listed in Table A.1 for testing.

Flickr popular set and Flickr common set both include 1000 randomly selected images annotated with over 20 tags from YFCC100M, but have different number of views for testing. Since tags defined by users usually have broad meanings. Besides the two Flickr dataset, we also prepare a dataset that tags are focused on visual content. We randomly select 1000 images from Wikimedia Commons [69]. Then using computer vision API provided by Microsoft Cognitive Services [70] for

annotation and utilizing them as original tags. In other words, all the tags are fully automatically annotated for MCS. Then we perform tag recommendations on these datasets.

A.5. Experimental Details

In the Table A.3, we show the example of recommendation tags on Flickr Popular dataset. The image is from YFCC100M, tags in the original column are defined by the original user who uploaded it. For images from YFCC100M dataset, original tags are defined by the original user who uploaded it.

Then we perform tag recommendations based on these original tags. In order to evaluate our recommendation results, we also perform recommendation base on other tag recommendation methods including Collaborative Filtering (CF) [62, 71], Tagcoor [72], and CF with DF-W [60].

In the Table A.2, we show the example of recommendation tags on MCS dataset. Here, the image is from Wikimedia Commons. Tags in the original column are extracted using computer vision API provided by Microsoft Cognitive Services. We use these tags as original tags, then we perform tag recommendations based on these original tags.

A.6. Online Evaluation

In the online evaluation process, we added 10 recommended tags to the original tag sets and uploaded to Flickr. Besides comparing the orignial tags with tags recommended by FPrank, we also compare with three other recommendation methods. In order to compare the evolution of popularity, for each recommendation method, we record the number of views of all the images every 12 hour in 10 days after uploaded.

The results are shown in Figure A.1, Figure A.2 and Figure A.3. We show average popularity of each image and images and average popularity obtained by each tag in each dataset. We can see that FPRank performed the best. For Flickr

TABLE A.2 – The example of tag recommendation results on MCS dataset.

(a) Image

(b) Original tags and Recommendations

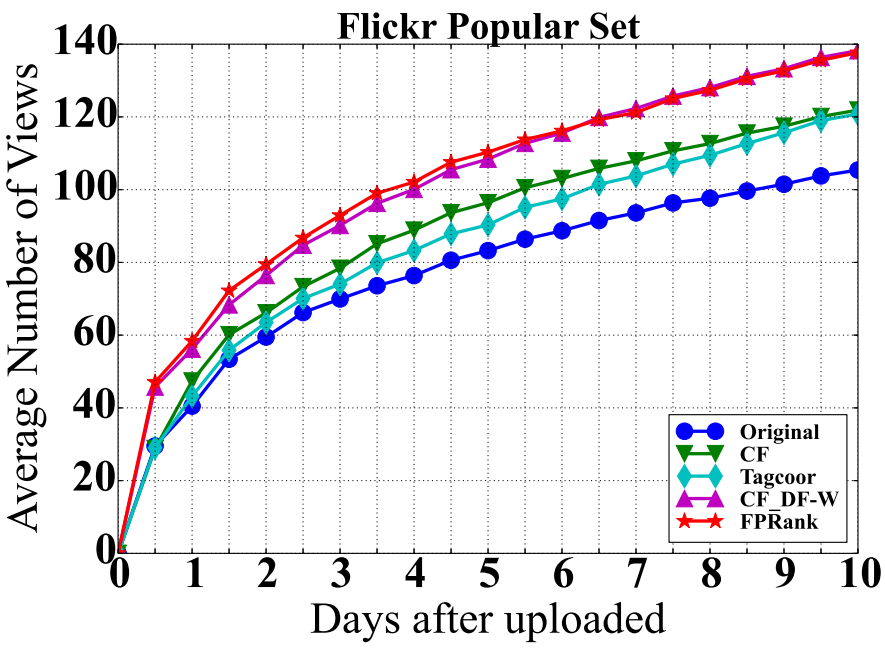
Recommendation Method	Tags
Original Tags	outdoor, building, road, house, street, small, orange, front, man, traffic, light, red ,group, game, walking, standing, large, holding, train, people, riding, sign, parked, board, track, city, white
Tagcoor	canon, photography, woman, blue, travel, portrait, art, nature, photo, black
CF	new york, urban, new, men, black, flag, downtown, girl, woman, york
CF_DF-W	girl, new york, woman, downtown, york, urban, flag, black, men, sri lanka
FPRank	blue, canon, woman, urban, black, nature, architecture, beautiful, photography, travel

TABLE A.3 – The example of tag recommendation results on Flickr Popular dataset.

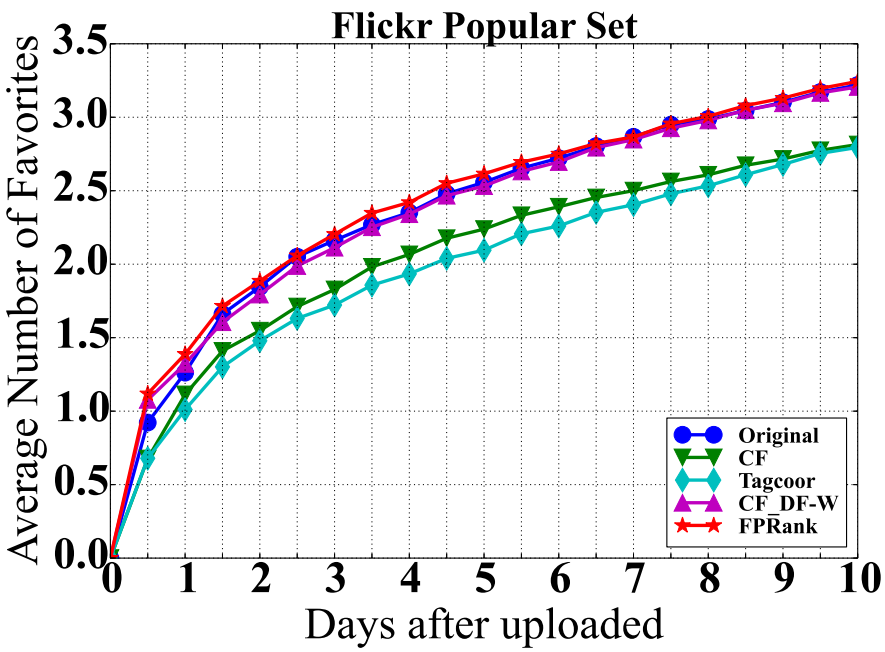
(a) Image

(b) Original tags and Recommendations

Recommendation Method	Tags
Original Tags	gravestones, headstones, leaves, sigma, shadows, leicester-shire, park, pdeee454, saint wistans, sunlight, sunshine, tombstones, trees, wistow, 17-70mm, 450d, canon, church, grass, kilby
Tagcoor	light, nature, sky, leaf, landscape, green, hdr, clouds, blue, sun
CF	nature, beach, water, australia, sky, sea, landscape, flowers, photography, clouds
CF_DF-W	landscape, beach, water, nature, girls, skyline, oregon, clouds, australia, sea
FPRank	hdr, light, nature, sky, landscape, sun, clouds, blue, green, water

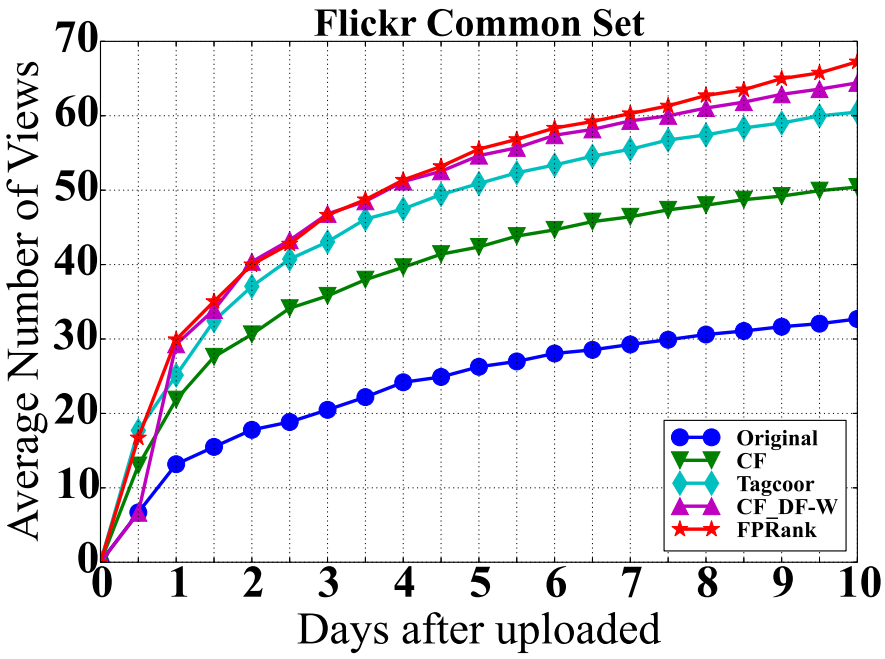


(a) average number of views of each image

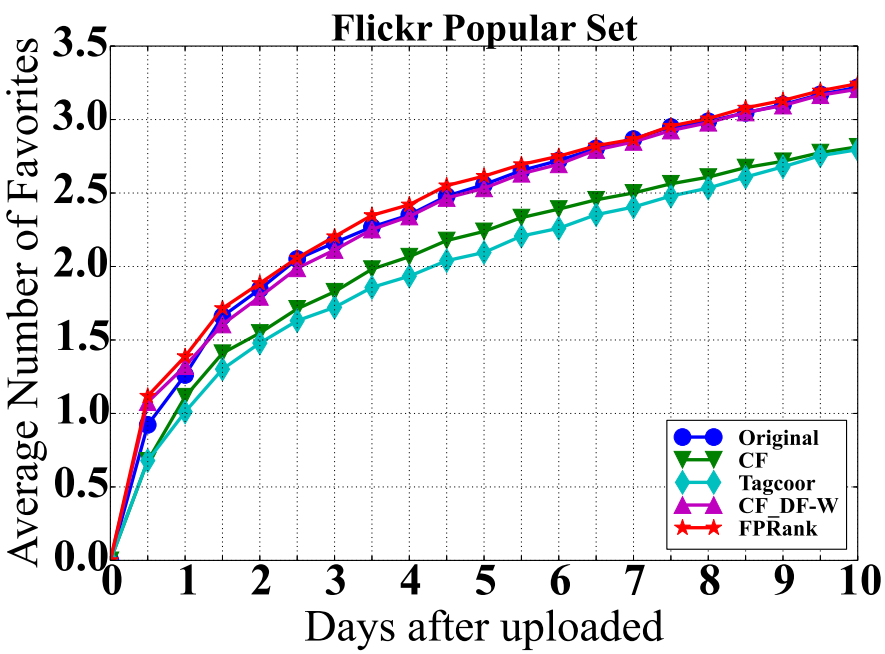


(b) average number of views obtained by each tag

FIGURE A.1 – Results of online evaluation on Flickr Popular dataset.



(a) average number of views of each image



(b) average number of views obtained by each tag

FIGURE A.2 – Results of online evaluation on Flickr Common dataset.

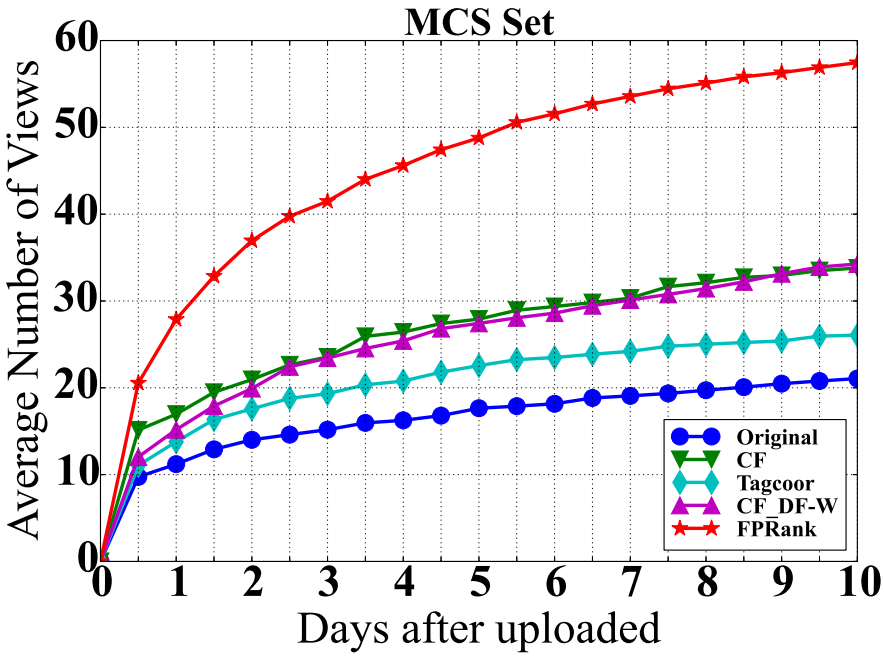
popular set, the average number of views is 1.4 times higher than that with the original tags, 2 times for Flickr common set, and 2.7 times for MCS set.

A.7. Results Analysis

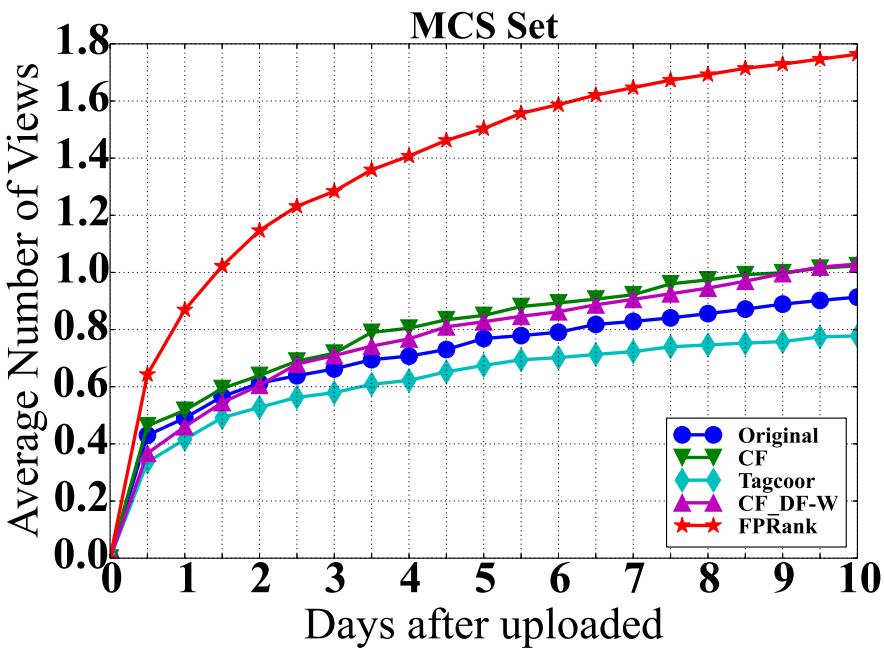
These results prove that FPRank makes better recommendations with a higher level of influence on popularity boosting over the other three tag recommendation methods. Comparing to Flickr datasets, we noticed that MCS dataset are much less popular. The main reason is that original tags in Flickr datasets are defined by people. And these tags are much popular than tags extracted by computer vision. It shows that FPRank has a better effect on popularity boosting in the unpopular test set.

A.8. Demo System

Figure A.4 shows a demo of our system. Users can search images from Flickr by the indicating the image ID. The system would offer 10 recommended tags generated by FPRank. The predicted number of views, comments, and favorites are calculated on the bottom. Users can modify tags based on the predicted social popularity score, to gain more attention.



(a) average number of views of each image



(b) average number of views obtained by each tag

FIGURE A.3 – Results of online evaluation on MCS dataset.

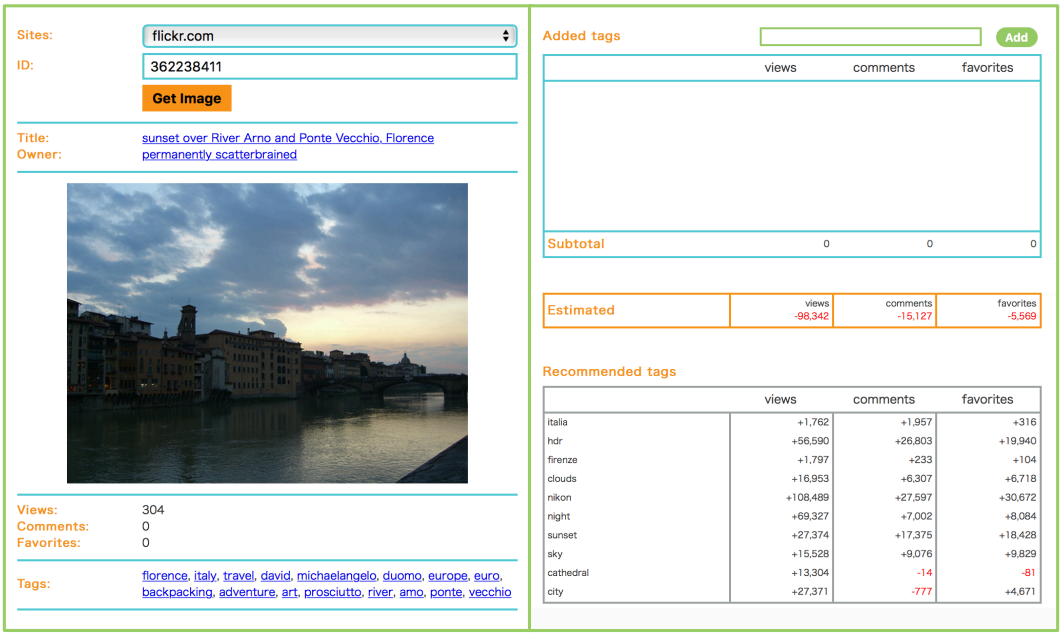


FIGURE A.4 – The Overview of Demo System

References

[1] A. M. Kaplan and M. Haenlein, "Users of the world, unite! the challenges and opportunities of social media," *Business horizons*, vol. 53, no. 1, pp. 59–68, 2010.

[2] https://www.omnicoreagency.com/twitter-statistics/.

[3] https://www.omnicoreagency.com/facebook-statistics/.

[4] https://www.instagram.com/press/.

[5] https://www.youtube.com/yt/press/statistics.html.

[6] A. Tatar, M. D. de Amorim, S. Fdida, and P. Antoniadis, "A survey on predicting the popularity of web content," *Journal of Internet Services and Applications*, vol. 5, no. 1, pp. 1–20, 2014.

[7] G. Szabo and B. A. Huberman, "Predicting the popularity of online content," *Communications of the ACM*, vol. 53, no. 8, pp. 80–88, 2010.

[8] A. Khosla, A. Das Sarma, and R. Hamid, "What makes an image popular?" in *Proceedings of the 23rd international conference on World wide web*. ACM, 2014, pp. 867–876.

[9] A. Piotrkowicz, V. Dimitrova, J. Otterbacher, and K. Markert, "Headlines matter: Using headlines to predict the popularity of news articles on twitter and facebook." in *ICWSM*, 2017, pp. 656–659.

[10] S. Jiang, X. Qian, T. Mei, and Y. Fu, "Personalized travel sequence recommendation on multi-source big social media," *IEEE Transactions on Big Data*, vol. 2, no. 1, pp. 43–56, 2016.

[11] K. Taylor, K. H. Lim, and J. Chan, "Travel itinerary recommendations with must-see points-of-interest," in *Companion of the The Web Conference 2018 on The Web Conference 2018*. International World Wide Web Conferences Steering Committee, 2018, pp. 1198–1205.

[12] J. Yang and B. Yecies, "Mining chinese social media ugc: a big-data framework for analyzing douban movie reviews," *Journal of Big Data*, vol. 3, no. 1, p. 3, 2016.

[13] Z. Zhao, Q. Yang, H. Lu, T. Weninger, D. Cai, X. He, and Y. Zhuang, "Social-aware movie recommendation via multimodal network learning," *IEEE Transactions on Multimedia*, vol. 20, no. 2, pp. 430–440, 2018.

[14] X. Zhang, J. Jia, K. Gao, Y. Zhang, D. Zhang, J. Li, and Q. Tian, "Trip outfits advisor: Location-oriented clothing recommendation," *IEEE Transactions on Multimedia*, vol. 19, no. 11, pp. 2533–2544, 2017.

[15] W. Yu, H. Zhang, X. He, X. Chen, L. Xiong, and Z. Qin, "Aesthetic-based clothing recommendation," in *Proceedings of the 2018 World Wide Web Conference on World Wide Web*. International World Wide Web Conferences Steering Committee, 2018, pp. 649–658.

[16] W. X. Zhao, S. Li, Y. He, E. Y. Chang, J.-R. Wen, and X. Li, "Connecting social media to e-commerce: Cold-start product recommendation using microblogging information," *IEEE Transactions on Knowledge and Data Engineering*, vol. 28, no. 5, pp. 1147–1159, 2016.

[17] R. Felix, P. A. Rauschnabel, and C. Hinsch, "Elements of strategic social media marketing: A holistic framework," *Journal of Business Research*, vol. 70, pp. 118–126, 2017.

[18] https://www.umassd.edu/cmr/social-media-research/2018-fortune-500.

[19] B. Shulman, A. Sharma, and D. Cosley, "Predictability of popularity: Gaps between prediction and understanding." in *ICWSM*, 2016, pp. 348–357.

[20] M. X. Hoang, X.-H. Dang, X. Wu, Z. Yan, and A. K. Singh, "Gpop: Scalable group-level popularity prediction for online content in social networks," in *Proceedings of the 26th International Conference on World Wide Web*. International World Wide Web Conferences Steering Committee, 2017, pp. 725–733.

[21] J. Hessel, L. Lee, and D. Mimno, "Cats and captions vs. creators and the clock: Comparing multimodal content to context in predicting relative popularity," in *Proceedings of the 26th International Conference on World Wide Web*. International World Wide Web Conferences Steering Committee, 2017, pp. 927–936.

[22] B. Wu, W.-H. Cheng, Y. Zhang, and T. Mei, "Time matters: Multi-scale temporalization of social media popularity," in *Proceedings of the 2016 ACM on Multimedia Conference*. ACM, 2016, pp. 1336–1344.

[23] B. Wu, T. Mei, W.-H. Cheng, Y. Zhang *et al.*, "Unfolding temporal dynamics: Predicting social media popularity using multi-scale temporal decomposition." in *AAAI*, 2016, pp. 272–278.

[24] B. Wu, W.-H. Cheng, Y. Zhang, Q. Huang, J. Li, and T. Mei, "Sequential prediction of social media popularity with deep temporal context networks," *arXiv preprint arXiv:1712.04443*, 2017.

[25] K. He, X. Zhang, S. Ren, and J. Sun, "Deep residual learning for image recognition," in *Proceedings of the IEEE conference on computer vision and pattern recognition*, 2016, pp. 770–778.

[26] J. Deng, W. Dong, R. Socher, L.-J. Li, K. Li, and L. Fei-Fei, "Imagenet: A large-scale hierarchical image database," in *Computer Vision and Pattern Recognition, 2009. CVPR 2009. IEEE Conference on*. IEEE, 2009, pp. 248–255.

[27] D. Sculley, "Web-scale k-means clustering," in *Proceedings of the 19th international conference on World wide web*. ACM, 2010, pp. 1177–1178.

[28] L. De Vries, S. Gensler, and P. S. Leeflang, "Popularity of brand posts on brand fan pages: An investigation of the effects of social media marketing," *Journal of interactive marketing*, vol. 26, no. 2, pp. 83–91, 2012.

[29] M. Mazloom, R. Rietveld, S. Rudinac, M. Worring, and W. Van Dolen, "Multimodal popularity prediction of brand-related social media posts," in *Proceedings of the 2016 ACM on Multimedia Conference*. ACM, 2016, pp. 197–201.

[30] G. Overgoor, M. Mazloom, M. Worring, R. Rietveld, and W. van Dolen, "A spatio-temporal category representation for brand popularity prediction," in *Proceedings of the 2017 ACM on International Conference on Multimedia Retrieval*. ACM, 2017, pp. 233–241.

[31] K.-Y. Goh, C.-S. Heng, and Z. Lin, "Social media brand community and consumer behavior: Quantifying the relative impact of user-and marketer-generated content," *Information Systems Research*, vol. 24, no. 1, pp. 88–107, 2013.

[32] M. Laroche, M. R. Habibi, M.-O. Richard, and R. Sankaranarayanan, "The effects of social media based brand communities on brand community markers, value creation practices, brand trust and brand loyalty," *Computers in Human Behavior*, vol. 28, no. 5, pp. 1755–1767, 2012.

[33] M. Laroche, M. R. Habibi, and M.-O. Richard, "To be or not to be in social media: How brand loyalty is affected by social media?" *International Journal of Information Management*, vol. 33, no. 1, pp. 76–82, 2013.

[34] A. J. Kim and E. Ko, "Do social media marketing activities enhance customer equity? an empirical study of luxury fashion brand," *Journal of Business Research*, vol. 65, no. 10, pp. 1480–1486, 2012.

[35] R. W. Naylor, C. P. Lamberton, and P. M. West, "Beyond the "like" button: The impact of mere virtual presence on brand evaluations and purchase intentions in social media settings," *Journal of Marketing*, vol. 76, no. 6, pp. 105–120, 2012.

[36] L. D. Hollebeek, M. S. Glynn, and R. J. Brodie, "Consumer brand engagement in social media: Conceptualization, scale development and validation," *Journal of interactive marketing*, vol. 28, no. 2, pp. 149–165, 2014.

[37] L. Dessart, C. Veloutsou, and A. Morgan-Thomas, "Consumer engagement in online brand communities: a social media perspective," *Journal of Product & Brand Management*, vol. 24, no. 1, pp. 28–42, 2015.

[38] S. Hudson, L. Huang, M. S. Roth, and T. J. Madden, "The influence of social media interactions on consumer–brand relationships: A three-country study of brand perceptions and marketing behaviors," *International Journal of Research in Marketing*, vol. 33, no. 1, pp. 27–41, 2016.

[39] C. Lopez and M. A. Leenders, "Building a local identity through sellout crowds: the impact of brand popularity, brand similarity, and brand diversity of music festivals," *Journal of Strategic Marketing*, pp. 1–16, 2018.

[40] X. Tang, Q. Miao, Y. Quan, J. Tang, and K. Deng, "Predicting individual retweet behavior by user similarity: A multi-task learning approach," *Knowledge-Based Systems*, vol. 89, pp. 681–688, 2015.

[41] M. Cheung, J. She, and Z. Jie, "Connection discovery using big data of user-shared images in social media," *IEEE Transactions on Multimedia*, vol. 17, no. 9, pp. 1417–1428, 2015.

[42] M. Bekk, M. Spörrle, and J. Kruse, "The benefits of similarity between tourist and destination personality," *Journal of Travel Research*, vol. 55, no. 8, pp. 1008–1021, 2016.

[43] A. Culotta and J. Cutler, "Mining brand perceptions from twitter social networks," *Marketing science*, vol. 35, no. 3, pp. 343–362, 2016.

[44] F. Gelli, T. Uricchio, X. He, A. Del Bimbo, and T.-S. Chua, "Beyond the product: Discovering image posts for brands in social media," in *Proceedings of the 2018 ACM on Multimedia Conference (MM'18). ACM*, 2018.

[45] T. H. Bijmolt, M. Wedel, R. G. Pieters, and W. S. DeSarbo, "Judgments of brand similarity1," *International Journal of Research in Marketing*, vol. 15, no. 3, pp. 249–268, 1998.

[46] P. Zhao, X. Xu, Y. Liu, V. S. Sheng, K. Zheng, and H. Xiong, "Photo2trip: Exploiting visual contents in geo-tagged photos for personalized tour recommendation," in *Proceedings of the 2017 ACM on Multimedia Conference*. ACM, 2017, pp. 916–924.

[47] C. Segalin, F. Celli, L. Polonio, M. Kosinski, D. Stillwell, N. Sebe, M. Cristani, and B. Lepri, "What your facebook profile picture reveals about your personality," in *Proceedings of the 2017 ACM on Multimedia Conference*. ACM, 2017, pp. 460–468.

[48] X. Han, Z. Wu, Y.-G. Jiang, and L. S. Davis, "Learning fashion compatibility with bidirectional lstms," in *Proceedings of the 2017 ACM on Multimedia Conference*. ACM, 2017, pp. 1078–1086.

[49] Y.-T. Chang, W.-H. Cheng, B. Wu, and K.-L. Hua, "Fashion world map: Understanding cities through streetwear fashion," in *Proceedings of the 2017 ACM on Multimedia Conference*. ACM, 2017, pp. 91–99.

[50] O. Barkan and N. Koenigstein, "Item2vec: neural item embedding for collaborative filtering," in *Machine Learning for Signal Processing (MLSP), 2016 IEEE 26th International Workshop on*. IEEE, 2016, pp. 1–6.

[51] T. Mikolov, I. Sutskever, K. Chen, G. S. Corrado, and J. Dean, "Distributed representations of words and phrases and their compositionality," in *Advances in neural information processing systems*, 2013, pp. 3111–3119.

[52] B. Eisner, T. Rocktäschel, I. Augenstein, M. Bošnjak, and S. Riedel, "emoji2vec: Learning emoji representations from their description," *arXiv preprint arXiv:1609.08359*, 2016.

[53] P. Bojanowski, E. Grave, A. Joulin, and T. Mikolov, "Enriching word vectors with subword information," *arXiv preprint arXiv:1607.04606*, 2016.

[54] K. Boakye, S. Farfade, H. Izadinia, Y. Kalantidis, and P. Garrigues, "Tag prediction at flickr: A view from the darkroom," in *Proceedings of the on Thematic Workshops of ACM Multimedia 2017*. ACM, 2017, pp. 376–384.

[55] G. Salton and M. J. McGill, "Introduction to modern information retrieval," 1986.

[56] R. Anand and D. Jeffrey, "Mining of massive datasets," 2012.

[57] W.-L. Hsiao and K. Grauman, "Learning the latent "look" : Unsupervised discovery of a style-coherent embedding from fashion images," in *2017 IEEE International Conference on Computer Vision (ICCV)*. IEEE, 2017, pp. 4213–4222.

[58] W.-L. Hsiao and K. Grauman, "Creating capsule wardrobes from fashion images," in *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 2018, pp. 7161–7170.

[59] https://crowdsourcing.yahoo.co.jp.

[60] T. Yamasaki, S. Sano, and K. Aizawa, "Social popularity score: Predicting numbers of views, comments, and favorites of social photos using only annotations," in *WISMM*, 2014, pp. 3–8.

[61] L. Hong, O. Dan, and B. D. Davison, "Predicting popular messages in twitter," in *Proceedings of the 20th international conference companion on World wide web*. ACM, 2011, pp. 57–58.

[62] X. Su and T. M. Khoshgoftaar, "A survey of collaborative filtering techniques," *Advances in artificial intelligence*, vol. 2009, p. 4, 2009.

[63] X. He, L. Liao, H. Zhang, L. Nie, X. Hu, and T.-S. Chua, "Neural collaborative filtering," in *Proceedings of the 26th International Conference on World Wide Web*. International World Wide Web Conferences Steering Committee, 2017, pp. 173–182.

[64] X. He, Z. He, J. Song, Z. Liu, Y.-G. Jiang, and T.-S. Chua, "Nais: Neural attentive item similarity model for recommendation," *IEEE Transactions on Knowledge and Data Engineering*, 2018.

[65] T. Yamasaki, J. Hu, S. Sano, and K. Aizawa, "Folkpopularityrank: Tag recommendation for enhancing social popularity using text tags in content sharing services," in *Proceedings of the 26th International Joint Conference on Artificial Intelligence*. AAAI Press, 2017, pp. 3231–3237.

[66] L. Page, S. Brin, R. Motwani, and T. Winograd, "The pagerank citation ranking: Bringing order to the web." Stanford InfoLab, Tech. Rep., 1999.

[67] A. Hotho, R. Jäschke, C. Schmitz, and G. Stumme, "Folkrank: A ranking algorithm for folksonomies," in *LWA*, vol. 1, 2006, pp. 111–114.

[68] B. Thomee, D. A. Shamma, G. Friedland, B. Elizalde, K. Ni, D. Poland, D. Borth, and L.-J. Li, "The new data and new challenges in multimedia research," *arXiv preprint arXiv:1503.01817*, pp. 3–10, 2015.

[69] https://commons.wikimedia.org/wiki/.

[70] https://azure.microsoft.com/en-us/services/cognitive-services/.

[71] P. Lops, M. De Gemmis, G. Semeraro, C. Musto, and F. Narducci, "Content-based and collaborative techniques for tag recommendation: an empirical evaluation," *Journal of Intelligent Information Systems*, vol. 40, no. 1, pp. 41–61, 2013.

[72] B. Sigurbjörnsson and R. Van Zwol, "Flickr tag recommendation based on collective knowledge," in *Proceedings of the 17th international conference on World Wide Web*. ACM, 2008, pp. 327–336.

Publications

International Conferences

[1] Toshihiko Yamasaki, Yiwei Zhang, Jiani Hu, Shumpei Sano, Kiyoharu Aizawa. Become Popular in SNS: Tag Recommendation using FolkPopularityRank to Enhance Social Popularity. *International Joint Conferences on Artificial Intelligence (IJCAI 2017)*, Demo, pp.5252-5253, Aug. 19-25, 2017, Melbourne, Australia.

[2] Yiwei Zhang, Toshihiko Yamasaki, Jiani Hu, Shumpei Sano, Kiyoharu Aizawa. A Tag Recommendation System for Popularity Boosting. *ACM Multimedia (ACMMM 2017)*, Demo, pp.1227-1228, Oct. 23-27, 2017, Mountain View, USA.

[3] Yiwei Zhang, Toshihiko Yamasaki, Jiani Hu, Shumpei Sano, Kiyoharu Aizawa. Computer Vision Based and FPRank Based Tag Recommendation for Social Popularity Enhancement. *ACM Intelligent User Interfaces (ACMIUI 2018)*, Demo, Mar. 7-11, 2018, Tokyo, Japan.

[4] Yiwei Zhang, Toshihiko Yamasaki, Kiyoharu Aizawa. Product and Service Popularity Analysis on Instagram. *IEEE International Conference on Consumer Electronics-Taiwan (ICCE-TW 2018)*, Best Paper Award Second Place.

Domestic Conferences and Symposia

[5] Yiwei Zhang, Toshihiko Yamasaki, Kiyoharu Aizawa. Product and Service Popularity Analysis and Class Discovery on Instagram. 電子情報通信学会 メディアエクスペリエンス・バーチャル環境基礎研究会, 信学技報, vol. 117, no. 217 MVE2017-16, pp. 13-18, Sep. 21-22, 2017, Chiba.

[6] Yiwei Zhang, Toshihiko Yamasaki, Kiyoharu Aizawa. Popularity Analysis on Instagram. 画像の認識・理解シンポジウム *(MIRU)*, PS1-35, Aug. 8-10, 2017, Hiroshima.

[7] Yiwei Zhang, Toshihiko Yamasaki, Kiyoharu Aizawa. Product and Service Popularity Analysis on Instagram. 映像メディア処理シンポジウム *(IMPS)*, P-3-9, Nov. 20-22, 2017, Shuzenji.

[8] Yiwei Zhang, Yoshiaki Sakai, Toshihiko Yamasaki. Measuring Similarity between Brands using Social Media Content. 電子情報通信学会 メディアエクスペリエンス・バーチャル環境基礎研究会, 信学技報, vol. 118, no. 211, MVE2018-16, pp. 19-24, Sep. 06-07, 2018, Osaka.

[9] 山崎俊彦, Xueting Wang, Yiwei Zhang, 竹田涼人. SNS によるメディア消費者の体験・行動センシング (Experience and Action Sensing of Media Consumers based on SNS). 情報系 *WINTER FESTA Episode4*, Dec. 25-26, 2018, 国立情報学研究所, 東京都千代田区. (予稿集なし)

[10] Yiwei Zhang, Xueting Wang, Yoshiaki Sakai, Toshihiko Yamasaki. Brand Relationship Analysis using Followers' Hash Tags and Images in Social Media Services. 画像工学研究会 *(IE)*, Feb. 20-21, 2019, Hokkaido, Submitted.

Awards

[11] 2018.04.17, ICCE-TW Best Paper Award Second Place.

Patents

[12] 山崎俊彦, Yiwei Zhang, "情報分析装置およびプログラム (SNS を用いた組織や人同士の距離計算手法)," 特願 2018-160577 (2018/08/29 出願).

Acknowledgements

I came to Japan two and a half years ago with worries and wishes. The memory of sitting in Narita Airport waiting for my first residence card in Japan is still very clear. I start my new life with two luggage suitcases. Looking back to the past time, I am glad to say that I have a wonderful experience at The University of Tokyo.

I take this opportunity to express my deepest appreciation to my supervisor, Prof. Toshihiko Yamasaki, for the patient guidance, monitoring and constant encouragement he has provided. I have been extremely lucky to have a supervisor who provided brilliant comments and suggestions, supported me through all the stages of the completion of this thesis. I have learned how to write the research paper step by step, and how to present the work to other people.

A special gratitude I give to Prof. Kiyoharu Aizawa, whose contribution in stimulating suggestions and encouragement helped me to coordinate research. Many thanks to the secretaries of our lab, Ms. Matsubayashi and Ms. Egawa, for their thoughtful kindness in both school affairs and daily life.

Thanks to all lab members, making this lab full of fun and laughter. Thanks to lab members who help check my poor Japanese writing and presentation slides. And I would like to express my sincere gratitude to those people who talk to me without regard to nationality. Having interesting talk with lab members, taking dinner together and playing super smash bros. are definitely unforgettable memories in my oversea life. Thanks to phD students, Saemi, Ikami, Furuta, Miyata, Sourav, Inoue, telling me about what is research and the attitude about it. Thanks to Hu, Lee, Shen, Onkar, students who provides help in many ways even after graduation. Thanks to students graduated from our lab, Marimo, Tsubame, Ted, help me learn other angle of Japan on Twitter. Thanks to Ogawa Toru, Ogawa Masanori, Tsubota, as friends of Nakayoshi-gohan.

Special thanks to the students of the same year, Obuchi, Ogawa, Takada, Nakamura, Narita, Goda, Tsukiyama, Otsubo, for the wonderful days we spent together. Thanks to Obuchi, who always help us book restaurants for Nakayoshi-Kai, and provide “interesting” story for all of us. Thanks to Ogawa, who help us

make travelling plans. Thanks to Takada, who is the creator of “pan-kun”, provide lots of laughter in this lab. Thanks to Nakamura, who always help check my poor Japanese writing patiently. Thanks to Narita, though always using strict word, the talking is interesting. Thanks to Goda, who is the ryoushi of our year. Thanks to Tsukiyama, who always answer my questions patiently. Thanks to Otsubo, though leave this lab a year before us, who is anthor ryoushi of our year. Wishing you all the best for the new beginning in your life. Hope to see you all after graduation:)

Finally, I wish to express my sincere thanks to my dear parents, who support me throughout the years, and allow me to choose the life I like.

Yiwei Zhang

January 30, 2019