Why do Instagram Users Tag Friends in Comments?

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ABSTRACT

Tagging a friend in a comment is one of the well-known mechanisms that leads user interaction in social media. This paper investigates the current practice of user tagging in Instagram by collecting a large-scale data that includes 9 K posts and their 4 M comments shared by 3 M users. Our analysis reveals that 54.8% of the comments contain user tagging, meaning that user tagging is widely-used in Instagram. To shed light on why Instagram users tag friends in comments, we develop a learning-based model that classifies the motivation of user tagging into one of the following motivations: (i) information-oriented, (ii) relationship-oriented, and (iii) discussion-oriented. We then apply our model to the comments with user tagging in our data, and reveal that user tagging is often used for interpersonal communication with friends.

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1 INTRODUCTION

Instagram is a popular image- and video-sharing online social network (OSN). Like many other OSNs such as Facebook, users in Instagram can share their feelings on the content with others through commenting to the posted content or other users' comments. As an interaction mechanism, Instagram allows a user to mention someone in a comment by writing '@' followed by the username, e.g., "@jwkang great photo!", which is called as 'user tagging'.

Tagging a friend in a comment is one of the well-known mechanisms that leads user interaction in OSNs [1, 3]. This in turn has led the research community to study the roles of user tagging, e.g., detecting users' social networks [2], promoting content [2], and fostering online communication [3]. However, little attention has been paid to understanding the motivations of user tagging in Instagram. Such research on the motivations of user tagging with empirically-grounded evidences can provide important insights for opinion leaders, marketers, or content providers who want to understand user responses and identify a set of (targeted) users with similar motivations/interests.

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To shed light on these issues, we investigate the current practice of user tagging in Instagram by collecting a large-scale user tagging data from Instagram that contains 9 K posts uploaded in the six popular categories (i.e., Funny, Game, Celebrity, Media, Nature, and Pet), and their 4 M comments shared by 3 M users. In our collected data, 54.8% of the comments contain user tagging, meaning that **user tagging is widely-used in Instagram**. We also find that 86.1% of the comments in the 'Funny' category have user tagging, implying a heavy usage of user tagging for the 'Funny' topic in Instagram. We then develop a learning-based model that classifies user tagging motivations and apply the model to the 1,236,027 comments with user tagging in our collected data.

2 USER TAGGING DATA

To analyze the practice of user tagging in Instagram, we first identified six popular categories of Instagram accounts – Funny, Game, Celebrity, Media, Nature, and Pet – by examining the business and content categories displayed in the 'Explore' menu of Instagram. Through exploring the articles about social media ranking reported in *Statista* [6] and *Social Blade* [5], we identified 27 Instagram accounts that have been regarded as popular and active ones who have many number of followers in the above categories. Finally, from the target accounts, we collected post information (post URL, posting time, posting username and userid, #comments and #likes) from January 1st to September 16th, 2018, and their comments information (displayed username, and text body of the comment that includes tagged username(s) if available), using the *InstaLooter API* and *Selenium WebDriver*. Our final data includes 9,501 posts and 3,913,575 comments written by 3,067,383 users.

3 MOTIVATION IDENTIFICATION

Based on prior research on user communication motivations in OSNs [3, 4], we assume that motivations of user tagging can be classified into one of the following three categories: (i) *informationoriented* that is for sharing the image or information given from the post, (ii) *relationship-oriented* for talking with their friends for fun, and (iii) *discussion-oriented* for having a discussion about the given post. To identify the motivation of user tagging in Instagram, we suggest to develop a learning-based model. Toward this end, we first randomly select two sets of 600 comments with user tagging (i.e., 100 comments per category), and assign two sets to two annotators. The annotators are instructed to classify the tagging motivation based on the following criteria.

Information-oriented: if a user talks about the information itself given from the post with tagged user(s), the motivation is classified as 'information-oriented'. For example, if a post shows an image about a dog wearing an avocado custom, and a user writes a comment like *"lol!! My favorite kind of avocado!!"* with user tagging, then the comment can be identified as 'information-oriented'.

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Table 1: A summary of model performance.

Features	Class	Accuracy	Precision	Recall	F1-Score
CMT	Information	0.82	0.79	0.84	0.82
	Relationship		0.85	0.79	0.82
	Discussion		0.81	0.85	0.83
CMT+POST	Information	0.76	0.78	0.82	0.80
	Relationship		0.78	0.74	0.76
	Discussion		0.65	0.65	0.65

Relationship-oriented: if a user has an interpersonal conversation with tagged user(s), and the post just mediates or fosters their conversations or even is not mentioned, the motivation is classified as 'relationship-oriented'. For instance, if a post is about a landscape photography, and a user writes *"Dan and I were saying we have to go with you guys one day"* with user tagging, then the comment can be identified as 'relationship-oriented'.

Discussion-oriented: If a user and their tagged user(s) have a discussion about the post, the motivation is classified as 'discussion-oriented'. For example, if a post shows a story about the right of minority religions, and a user writes *"except its a ploy to cast established religions in a negative light. Parody is not a religion"* with user tagging, then the comment can be classified as 'discussion-oriented'.

To improve the credibility on the results classified by each annotator, we only use the comments with user tagging which are identified as the identical label by two annotators, and also exclude the comments that cannot be labeled with the above instructions. Finally, we obtain 747 comments with one of the following labels: 'information-oriented' (313; 42%), 'relationship-oriented' (369; 49%), and 'discussion-oriented' (65; 9%).

4 TAGGING MOTIVATION CLASSIFICATION

We now develop a learning-based model with the above labeled data to classify the motivation of user tagging.

4.1 Model

In our model, we consider the following sets of input features.

- *CMT* features are extracted from a comment text, including word count, LIWC sentiment scores for the comment text, the existence of the emoji, and the portion of the emoji out of all the words in the comment.
- *POST* features indicates the information about the post, including word count, LIWC sentiment scores for the post text, the category of the post, the numbers of likes and comments for the post, and the frequencies of the top 3 hashtags in the uploaded post.

We consider various popular classifiers such as the SVM and Random Forest in our model, but we use the XGBoost as it performs the best. Note that we apply the grid search algorithm with performing a 5-fold cross-validation to optimize the hyper-parameters for the classifier. Since three classes (motivations) have different numbers of instances (e.g., 'discussion-oriented' (9%) vs. 'relationshiporiented' (49%)) in learning, we apply the SMOTE in the learning phase to address the class imbalance problem.

4.2 Model Performance

Table 1 summarizes the model performance based on *CMT* and *CMT+POST* features. As shown in Table 1, *CMT* features alone



Figure 1: Classification results on the motivations of user tagging across the categories.

achieves higher performance than *CMT+POST* features, which implies that suggested comment features are identified as the good predictors for classifying user tagging motivations. Therefore, our final model is trained with *CMT* features.

4.3 Tagging Motivation Analysis

We apply our model to the 1,236,027 comments with user tagging in our data. Figure 1 shows the portion of 'information-oriented', 'relationship-oriented', and 'discussion-oriented' comments across the categories. As shown in Figure 1, a large portion of comments with user tagging is for sharing information (i.e., 'informationoriented'), especially in the Pet and Funny categories. On the other hand, there are more 'relationship-oriented' comments than 'information-oriented' comments in the Game category, meaning that users who are interested in Game topics tend to tag their friends more for their interpersonal communication. A substantial portion of comments with user tagging tends to discuss about the posts in the Game, Media, Celebrity, and Nature categories whereas 'discussion-oriented' comments are hardly observed in the Pet and Funny category. Overall, 54.8 %, 40.0 %, and 5.2 % of comments with user tagging are 'information-oriented', and 'relationship-oriented', and 'discussion-oriented', respectively. This reveals that user tagging is often used for interpersonal communication among friends; a substantial portion (40.0%) of the comments with user tagging are identified as 'relationship-oriented'.

5 CONCLUDING REMARKS

This paper investigated the current practice of user tagging in Instagram. We found that 54.8% of the comments contain user tagging, signifying that user tagging is widely-used in Instagram. By analyzing user tagging motivations using our proposed model, we reveal that user tagging is often used for interpersonal communication among friends. Our ongoing work includes (i) developing a model that identifies target users based on their comments (with user tagging) for targeted marketing and (ii) investigating how user tagging can be used for product recommendations.

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