Towards Understanding User Preferences from User Tagging Behavior for Personalization

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Abstract—Personalizing image tags is a relatively new and growing area of research, and in order to advance this research community, we must review and challenge the de-facto standard of defining tag importance. We believe that for greater progress to be made, we must go beyond tags that merely describe objects that are visually represented in the image, towards more user-centric and subjective notions such as emotion, sentiment, and preferences.

We focus on the notion of user preferences and show that the order that users list tags on images is correlated to the order of preference over the tags that they provided for the image. While this observation is not completely surprising, to our knowledge, we are the first to explore this aspect of user tagging behavior systematically and report empirical results to support this observation. We argue that this observation can be exploited to help advance the image tagging (and related) communities.

Our contributions include: 1.) conducting a user study demonstrating this observation, 2.) collecting a dataset with user tag preferences explicitly collected.

Keywords-tagging; behavior; personalization; user preference

I. INTRODUCTION

With the proliferation of cheap imaging devices (e.g., smartphone cameras, point-and-shoots, SLRs and DSLRs) and content sharing websites (e.g., Flickr, Tumblr, Instagram, etc), the size of personal image collections has been growing rapidly, making it unfeasible for users to manually tag all images in their collections. For example, on average, 130 million images are uploaded on Tumblr [1] and more than 90% of those images have no identifying text or tags [2]. This makes the task of automatic image annotation all the more important, and with the lack of semantic understanding of images (“semantic gap”) this task becomes very difficult.

Much of the work in automatic image tagging has ignored the user factor [8]–[12] by trying to find what we denote as statistical correlations between the image content (visual features) and objective semantics regardless of the particular users involved in the tagging activity. There has been some work that focuses on user personalization in automated image tagging, most notably, [5], which we consider as the state-of-art in this domain. Along the lines of object importances as they relate to tags, the focus has mainly been on an explicitly categorical definition of importance by measuring properties of content/objects in the image (e.g., size, salience, etc) to estimate their relative importances [13]. These content property based approaches to importance also tends to ignore particular user effects and preferences, treating importance as a purely global phenomenon [13], [14]. In our day and age where content is increasingly personalized and tailored to user tastes, we believe that it is of paramount importance to systematically understand user tagging behavior and trends.

A recent attempt at a design change on Flickr [15], and the subsequent reversal of the change, demonstrates our second assumption. The Flickr designers opted to update the site to present user generated tags in reverse-chronological order, and immediately active Flickr users protested this change, citing that the order that they presented their tags was intentional [16], leading to an apology by the designers and a reverting back to the original chronological order design. This event lead us to believe when providing tag lists, users are not merely motivated by visually measurable properties such as saliency, but more so by implicit biases and preferences which are in turn reflected in the order of tagging list.

In the subsequent sections, we investigate our aforementioned hypotheses via a user study conducted using the Amazon Mechanical Turk (AMT) system, and compare to more popular global notions of importance.

A. Related Works

There are two ways to approach image tagging. First, explicit object tagging, where an image is tagged with a particular word if the object the word represents is detected as being in the image. Second, implicit tagging, where the query image is compared to other similar images, and the tags are “transferred” from the most similar images to the query image, via some scoring function. Many applications of this implicit approach take their cue from the world of collaborative filtering [10], [7].

The implicit approaches are usually more common than their explicit counterparts because one does not have to learn how to recognize or detect specific objects in the image, which as earlier noted is not scalable, also not all concepts one would like to use in describing an image are necessarily visual (semantic gap) [18], [19]. Also, with the implicit approaches one could imagine a latent space that more readily embeds some sense of relatedness [10], while on the explicit end, it is
harder to extrapolate a measure of relatedness between objects of different classes.

With regards to personalization in image tagging, in the work by Rendle et al. [20], they assume that tag mentioned are preferred to those unmentioned. This is similar to our assumption but they treat the tags that appear together on a tagging list equally, which our work here suggests not to do. In the work by Lipczak et al. [21] they also treat tags as essentially structureless entities (bag of words), and other work on personalization similarly treat user provided tag lists as such [5], [21]. To our knowledge, we are the first to suggest that these user provided list should be treated as having structure.

II. USER STUDY

In order to verify our assumption that users tend to place the tags they prefer or consider most important at the start of tag lists, we found it prudent to conduct a live user experiment using the AMT system. Our main metric of interest is the rank correlation between tags lists when we explicitly request and ascertain the preference order of tags they provided for an image, versus the order of the same tags without such a prompt for ranking their preferences. In the following, we will detail the setup of our user study, our metrics and measurements, comparison to other measures of (global) importance, and our conclusions from the user study.

A. Study Setup

We conducted our study on a subset of 500 images from the NUS-WIDE dataset [22] which is a dataset of images from the popular photoblogging website Flickr [15]. These images were divided into 100 groups of 5 to create 100 Human Intelligence Tasks (HITs), which is the smallest indivisible unit of work on AMT. Each HIT was then assigned to 15 different study participants (turkers), totaling 1500 assignments.

For each HIT, our study was done in 2 stages as shown in Fig. 1. In the first stage, we asked the turker to provide 5 tags for each of the 5 images contained in the HIT, we refer to this as the Tag Allocation Stage. The tags are allocated for all of the 5 images before we begin the next stage of the experiment. In the second stage of the study, we iteratively asked the turker to eliminate their least preferred tag for each image from the set of tags that had not yet been eliminated for that image in previous iterations. For each round of elimination, we randomly scrambled the order of the tags that were left from previous rounds to prevent turkers from any influence of presentation bias. Similarly, the order of the images in each elimination round was randomly shuffled to prevent presentation bias. We refer to the second stage as the Preference Allocation Stage.

We also added a hidden verification test as part of the preference allocation stage to ensure that the preferences which the turker provided were consistent when asked a second time. To that end, after reconstructing their preference order from 4 elimination rounds, for each image, we asked the turker to eliminate their least preferred tag among 2 randomly chosen tags of those which the user had provided for that image. If their response matched their reconstructed preference order, then we considered the user’s preference order for that image verified otherwise not. So within each HIT we can tell which of the reconstructed preference lists are reliable, and so on the level of HITs we can define the HIT reliability as the number of verified preference orders within the HIT.

At the end of the experiment we are left with 7500 pairs of tag lists from 391 turkers. Each tag list pair consists of a tag list in the default order and the same tags in the user’s preferred order. And for each of those pairs we know whether or not the preferred order is verified and use that as a proxy to its reliability.

B. Metrics and Measurements

To verify our assumption that users tend to present their tag lists with an inherent preference order as opposed to being an orderless set or bag-of-words, we examine the data collected from our AMT user study. To measure whether the data supports our claim, we employ 2 metrics: 1.) Kendall’s Tau Rank Correlation [23], and 2.) Spearman’s Rho Rank Correlation [24], which are both measures of how much two rankings are correlated with one another. Both measures range from -1 to 1, with -1 indicating perfect negative correlation, 0 indicating no correlation, and 1 indicating perfect positive correlation.

We measure the average correlation per user, and the average correlation per image. We also measure the effect of the verification of the preference order on the correlation scores, and report our final numbers based on data that has been reasonably verified. We also present the confusion matrix.
This figure shows the confusion matrix between the preferred position of tags (groundtruth label) and the initial position of tags (predicted label) at different levels of verification per HIT. The verification level is the number of images (out of 5) that were verified within the hit.

This table shows the correlation statistics between the initial rank of tags, and the preference ranks as provided by the user. We provide the averages per assignment, per user (averaging over all images for the user), and per image (averaging over all users for that image).

### TABLE I

|                  | Avg. τ corr | Var. τ corr | Avg. ρ corr | Var. ρ corr | min. verification/total | num verified/total |
|------------------|-------------|-------------|-------------|-------------|-------------------------|-------------------|
| Per Assignment   | 0.3089      | 0.062       | 0.3705      | 0.083       | 4/5                     | 1114/1500         |
| Per User         | 0.3046      | 0.047       | 0.3652      | 0.064       | 3.5/5                   | 298/391           |
| Per Image        | 0.2840      | 0.017       | 0.3400      | 0.021       | 11/15                   | 434/500           |

between the position “labels”, that is, assuming each tag is labeled with it’s position from the initial order, how well does its position “label” on the preference order list predict its position “label” from the initial order.

As we can see from the confusion matrices in Fig. 2, assuming that the verification level (here as the number of images verified within a single HIT) is a proxy of the turker’s attention to the task (and hence reliability), the position of a tag on the initial list is a good predictor of the position of the tag according to the turker’s preference. As the reliability increases, more often than not, the initial position is the same as the preferred position, and any “mislabeling” is typically within an error of 1 position.

In Fig. 3 we see that from the reliable HITs, there seems to be a moderately high correlation (which is statistically significantly different from being uncorrelated, as validated by a two-sided 1 sample t-test with p-values less than 0.01) between the initial tag list, and the reconstructed preference order, and we believe we are the first to show empirically, the existence of such phenomenon, which apriori is not so obvious.

Each image is tagged by 15 different turkers, and most of the images, more often than not, were tagged reliably by the turkers. From Fig. 4 we can see that the aforementioned correlation is largely independent of the image, as even those images with less reliable preference orders show a moderate correlation between the reconstructed preference tag order and the initial tag list, so it doesn’t seem to be the case that image visual content itself is the cause of the correlation. When we consider the average correlation per user as is shown in Fig. 5 we also observe the similar trend that users that have tagged images more reliably show on average a moderately high correlation between the reconstructed preference order, and even the less reliable users still exhibit a slight correlation as well. Our results are summarized in Table II and these are statistically significant as verified by a one sample t-test with respect to 0 correlation.

### C. Comparison to Global Importance

In much of image tagging research [5], [13], [14], [25], [26], tag importance is usually considered in terms of what is visually represented in the image, and typically by saliency. To that end, many researchers use tag frequency as a proxy to tag importance and saliency [14], [25], and for nearest neighbor approaches to tagging, predicting the tags that are based on the most frequent has had relative success in terms of tag recall [5].

In this section, we compare the reconstructed user preference order to the frequency order gotten from the number of times the tag was mentioned by turkers for that image. In Table II we report the correlation statistics. As we can see, there is a slight correlation between the preference and the frequency, but it is not that strong, which suggests that although users might mention tags of global importance (or
This table shows the correlation statistics between the frequency rank of tags, and the preference ranks as provided by the user. The frequency rank of a tag for an image is derived from the number of times it was mentioned by all the turkers that tagged the given image. We provide the correlation statistics over all the tag list, and also averaged across the users for each image. We only report the statistics for images that were verified, using all the images results in even lower correlation.

Fig. 3. This figure shows the average correlation (and error bars) between the initial tag list, and the reconstructed preference order with respect to the level of reliability. The Kendall’s Tau correlation is shown on the left, and Spearman’s Rho on the right.

Fig. 4. This figure shows the average correlation per image (and error bars) between the initial tag list, and the reconstructed preference order with respect to the number of times the image has been reliably tagged. The Kendall’s Tau correlation is shown on the left, and Spearman’s Rho on the right.

In order to verify that suggestion, we also report the average position of the most frequently mentioned tag for an image on the reconstructed preference ordered list for the same image and notice that more often than not, the most frequent tag is usually mentioned later in the preference order as is seen in Table III.

D. Study Summary

From our study we arrive at the following conclusions: 1.) The order that users provide in their tag list for an image is moderately correlated to their inherent preferences over those tags, 2.) This preferred order is not as simple as the order

|                | Avg. $\tau$ corr | Var. $\tau$ corr | Avg. $\rho$ corr | Var. $\rho$ corr |
|----------------|------------------|------------------|------------------|------------------|
| Overall        | 0.187417923625   | 0.177135465861   | 0.220259416265   | 0.232534427034   |
| Image (avg. over users) | 0.186084678459 | 0.0230843379766 | 0.218679398053   | 0.0306837413827   |
of objects in the image from most salient to least salient, nor the same as other global notions of preference, and 3.) Hence in understanding user tagging behavior and inferring user preferences, one should consider the order that users present their tags for images.

We believe that this study will help further the development of research in the area of image tagging, and that using the observations provided by this study, could improve upon current state-of-art methods for image tagging, especially with respect to personalization.

III. CONCLUSION AND FUTURE WORK

In this work we proposed a new measurement of tag preferences, and demonstrated that there is indeed a tag-order bias, that is, when a user mentions tag a before tag b, in a list of tags for a given image, the user is implying that he/she prefers, or considers a to be of greater importance than b. This leads us to conclude that although there are many visual factors that may affect what tags a user will provide for an image, it is more useful to characterize instead (or rather in conjunction with) the users’ tagging habits to learn what tags are of more importance to the users, whether visually motivated or not, and automatic tagging systems should employ this technique to improve their overall performance.

It is also important to note that this study was not tied to any particular online tagging system, like Flickr, and as such we believe that the findings in this study are independent of the online platform, as opposed to being an artifact of the user interface. Hence, the findings should hold on most online tagging systems, or at least image tagging systems that allow for user input via text. One direct way we believe this preference information can be exploited is, given a user’s tagging history, if tags a and b frequently occur on the same tag lists for images, and tag a is mentioned before b more often than the reverse, in predicting a tag list for a new image for that user, this preference order should be enforced as it reflects a preference for a over b for that user.

Another future direction, assuming we can embed the tags into some metric space, is, we believe it would be interesting to learn a function that takes as input, a pair of features (each representing a tag) and returns a prediction of the pair preference order and strength. This will enable us to “transfer” preferences between tags that are similar (or closely related) even though we might never have observed them together for a particular user. We would also like to analyze what kinds/categories of tags are preferred over others under this framework, and answer the question, do these categorical relationships depend on the user (i.e., do the users cluster in a way such that the different clusters exhibit different categorical relationships)? For example do some user tend to tag images in a bottom-up fashion with respect to ontologies, and other users in a top-bottom fashion?

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