Privacy-Aware Tag Recommendation for Image Sharing

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Image Privacy Prediction?

- Rapid increase in social media can cause threat to user's privacy
- Many users are quick to share private images without realizing the consequences of an unwanted disclosure of these images.
- Users rarely change default privacy settings, which could jeopardize their privacy [Zerr et al., 2012].
- Current social networking sites do not assist users in making privacy decisions for images that they share online.
- Image Privacy Prediction predicts privacy setting for images and avoid a possible loss of users' privacy.

Prior Works

- Recently, [Squicciarini et al., 2014] and [Zerr et al., 2012] found that user tags are informative for classifying images as *private* or *public*.
- [Tonge and Caragea, 2016, Tonge and Caragea, 2018, Tonge et al., 2018] automatically obtained image tags from the visual content using convolutional neural networks and also showed their performance for privacy prediction.

Motivation

(a) *Private*, Elegant Corporate, Style Fashion, Girl, Woman Skirt, Top, Bag, Pretty

(b) *Public*, Parisi, Sabrina News, Celebrity Famous, Girl Woman, Hollywood

Figure: Anecdotal evidence for visually similar images with privacy-aware user tags.

Our Contributions

- Present a privacy-aware approach to image tagging.
  - Improve the quality of user tags.
  - Preserving the images original privacy sharing patterns.
- Recommends potential tags for a target image by mining privacy-aware tags from the most similar images.
- Although the user-input tags comprise noise or even some images do not have any tags at all, our approach is able to recommend accurate tags.
- Results show that the predicted tags can exhibit relevant cues for specific privacy settings.

Datasets

- We evaluated our approach on Flickr images sampled from the PiCalert dataset [Zerr et al., 2012].
- PiCalert consists of Flickr images on various subjects, which are manually labeled as *public* or *private* by external viewers.
- The public and private images are in the ratio of 3:1.
- *Private*: Private image discloses sensitive information about a user. E.g., images with self-portraits, family, friends, someone's home, etc.
- *Public*: Remaining images are labeled as public.

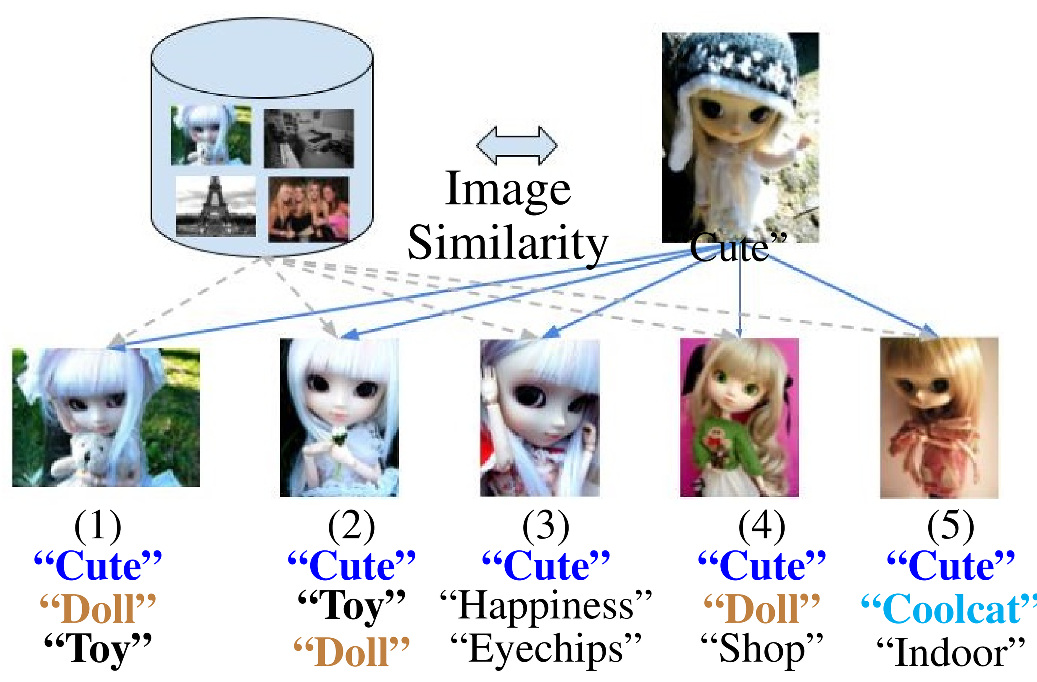
Dataset	#Total Images	#Avg. Tags	#min. Tags	#max. Tags	#Pr.	#Pu.
$(\mathfrak{D})$	8000	9.73	1	71	2000	6000
DS_1	3689	16.60	11	78	922	2767
DS_2	500	20.70	11	69	125	375

Table: Datasets summary.

Privacy-Aware Image Tag Recommendation

- Our approach draws ideas from collaborative filtering (CF).
- The analogy with conventional CF methods is that images correspond to users and tags correspond to items.
- Base our models on the assumption that privacy-aware similar images possess similar tags Online Image Privacy.
- Images can be represented using two different views or feature types: (1) image visual content and (2) image tags.

Algorithm Illustration - I



Recommended Tags - "Doll," "Toy," "Coolcat"

Figure: Illustration of the privacy-aware tag recommendation algorithm using an example.

Algorithm Illustration - II

Candidate Tags	Count	$P(t\|pr = private)$	$P(t\|pr = public)$	w_t $s_j = 1$
Doll	**3**	**0.1**	**0.9**	**3 × 0.9 = 2.7**
Toy	**2**	**0.15**	**0.85**	**2 × 0.85 = 1.7**
Cute	**5**	**0.7**	**0.3**	**5 × 0.3 = 1.5**
Coolcat	**1**	**0.0**	**1.0**	**1 × 1.0 = 1.0**
Shop	1	0.0	1.0	1 × 1.0 = 1.0
Eyechips	1	0.3	0.7	1 × 0.7 = 0.7
Indoor	1	0.6	0.4	1 × 0.4 = 0.4
Happiness	1	0.6	0.4	1 × 0.4 = 0.4

Table: Privacy-aware weighted sum of tag occurrences ($K = 5$, $r = 3$).

Experiments and Results

Evaluation by Privacy Prediction

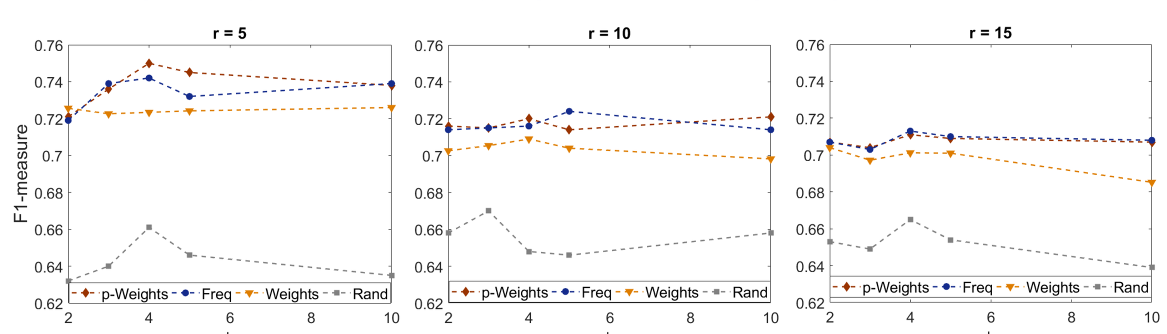


Figure: F1-measure obtained for various parameter values of scoring methods, k and r.

Features	Acc. %	F1	Precision	Recall
vt	74.83	0.743	0.739	0.748
		$k = 4$		
vt & $rt(5)$	**77.84**	**0.766**	**0.755**	**0.778**
vt & $rt(10)$	77.47	0.763	0.752	0.776
vt & $rt(15)$	77.31	0.757	0.744	0.771
vt & $rt(20)$	76.83	0.754	0.741	0.769
		$k = 5$		
vt & $rt(5)$	**77.96**	**0.769**	**0.758**	**0.781**
vt & $rt(10)$	77.80	0.766	0.755	0.778
vt & $rt(15)$	77.60	0.764	0.752	0.776
vt & $rt(20)$	77.27	0.760	0.747	0.773
		$k = 10$		
vt & $rt(5)$	**78.20**	**0.772**	**0.762**	**0.783**
vt & $rt(10)$	77.80	0.765	0.754	0.777
vt & $rt(15)$	77.92	0.767	0.758	0.778
vt & $rt(20)$	77.43	0.758	0.745	0.771

Table: Performance for privacy prediction after adding recommended tags.

Experiments and Results

Cold Start Problem

Features	Acc.%	F1	Precision	Recall
$pool_5(rt)$	**75.74**	0.743	0.729	**0.757**
DT(rt)	74.19	0.731	0.725	0.742
vt	74.83	0.743	0.739	0.748
DT	68.54	0.645	0.619	0.685

Table: Visual content-based similarity ($k = 10$).

Proposed Approach vs. Prior Works

Features	Acc.%	F1	Precision	Recall
	#1 Original User Tags (Visible Tags)			
vt	74.83	0.743	0.739	0.748
	#2 FastTag (Prior work)			
vt & rt	74.55	0.741	0.738	0.745
	#3 Visual Content Similarity ($T = \phi$)			
vt & $rt(5)$	75.23	0.741	0.730	0.752
vt & $rt(10)$	75.63	0.742	0.727	0.757
vt & $rt(15)$	***76.71***	***0.752***	***0.737***	***0.768***
vt & $rt(20)$	76.27	0.747	0.732	0.763
	#4 Tag Similarity ($T \neq \phi$)			
vt & $rt(5)$	**78.20**	**0.772**	**0.762**	**0.783**

Table: Privacy-aware Tag recommendation vs. FastTag.

Quality Assessment of Recommended Tags

#Tags (r)	Gold-standard P@r	User-Study P@r
1	0.177	**0.855**
2	**0.181**	0.761
3	**0.181**	0.755
4	0.172	0.703
5	0.174	0.691
10	0.155	0.633

Table: Gold-standard and User evaluation of recommended tags.

Visible	Hidden	Recommended Tags	
Beauty	Geisha	**People**	*Culture*
Light	Kyoto	**Japan**	*Street*
Travel	Japan	**Asia**	*Walking*
Couple	Kimono	**Geisha**	
Woman	Traditional	**Kimono**	
Vintage	Asia	**Kyoto**	
	People	**Traditional**	

Figure: Image with recommended tags, r=10.

Conclusions

- Improve the original set of user tags and preserve images privacy.
- Draw ideas from collaborative filtering (CF).
- Although the user-input tags are prone to noise, we were able to integrate them in our approach and recommend accurate tags.
- Simulated the recommendation strategy for newly-posted images, which had no tags attached.
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- Achieved better performance for privacy prediction with recommended tags than user tags.
  - Indicate that the suggested tags comply to the images privacy.
- Conducted a user evaluation of recommended tags to inspect the quality of the recommended tags.
  - Results show that the proposed approach is able to recommend highly relevant tags.
- Future directions
  - Multiple sharing needs of the user.
  - Computing images similarity by combining both tags and visual content.

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