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Image Privacy Prediction Using Deep Features

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Why 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.
- Manually assigning privacy settings to each image every time can be cumbersome.
- Image Privacy Prediction predicts privacy setting for images and avoid a possible loss of users' privacy.

Previous Approaches to Image Privacy Prediction

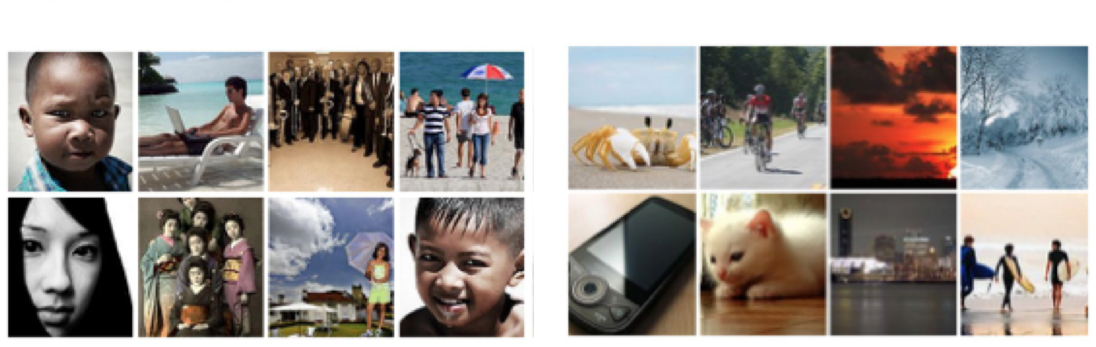
- Most existing privacy prediction techniques used user tags and image content features such as SIFT (or Scale Invariant Feature Transform) and RGB (or Red Green Blue) [Zerr et al., 2012, Squicciarini et al., 2014]
- Buschek et al. [Buschek et al., 2015] presented an approach to assigning privacy settings to shared images using metadata (location, time, shot details) and visual features (faces, colors, edges).
- Several works were conducted in the context of tag-based access control policies for images [Yeung et al., 2009, Klemperer et al., 2012, Vyas et al., 2009]
  - However, the scarcity of tags [Sundaram et al., 2012] precluded accurate analysis of images' sensitivity.
- We posit that, given large dataset of labeled images e.g., the ImageNet dataset [Russakovsky et al., 2015], user tags and SIFT features may not work well. However, deep neural networks are now able to learn powerful deep features [Jia et al., 2014] that go beyond SIFT and RGB, and have potential to improve privacy prediction.

Our Contributions

- In this study, we explore an approach to image privacy prediction based on **deep visual features** and **deep tags**.
- Empirically, deep features and deep tags outperforms baseline approaches SIFT, GIST, and user provided tags.
- Models trained on "SIFT" and "GIST" yield very low performance with respect to the private class.
- Combination of deep tags and user tags performs better than their individual performance.
- We evaluate our approach on Flickr images sampled from the PiCalert dataset [Zerr et al., 2012].
- Tag analysis can assist in understanding the characteristics of the private and public classes.

Datasets

- We evaluated our approach on a subset of 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.
- We selected 5,000 images from PiCalert randomly, out of which only 4,700 have user provided tags and these 4,700 images were used for our privacy prediction task.
- The public and private images are in the ratio of 3:1.



(a) Private (b) Public

Figure: Examples of private and public images from PiCalert dataset.

Private: Private image discloses sensitive information about a user. E.g., images with portraits, people on the beach, family photos, etc.

Public: Public images generally depict scenery, objects, animals, etc., which do not provide any personal information about a user.

Proposed Approach: Privacy Prediction

- Feature Extraction
  We extracted visual features and tags for differentiating between private and public classes.
  - **Deep Visual Features**
  - In the convolutional neural network (CNN) architecture, features are extracted from images through each layer in a feed-forward fashion.
  - The architecture consists of eight layers; the first five layers are convolutional and the remaining three are fully-connected (FC).
  - The last two fully connected layers are referred as FC_7 and FC_8. and used as *deep visual features* for images.
  - The output layer "Prob" is obtained from the output of FC_8 via a softmax function, which produces a probability distribution over the 1000 object categories.
  - **Deep Tag Features**
  - for an image, we predict top k object categories from the probability distribution over categories, i.e., the "Prob" layer of the deep neural network.
  - The k predicted categories are used as tags to describe an image.
- Feature Classification
  Using above feature representations, we train maximum margin (SVM) classifiers and use them to predict the class of an image as *private* or *public*

Proposed Approach: Feature Extraction

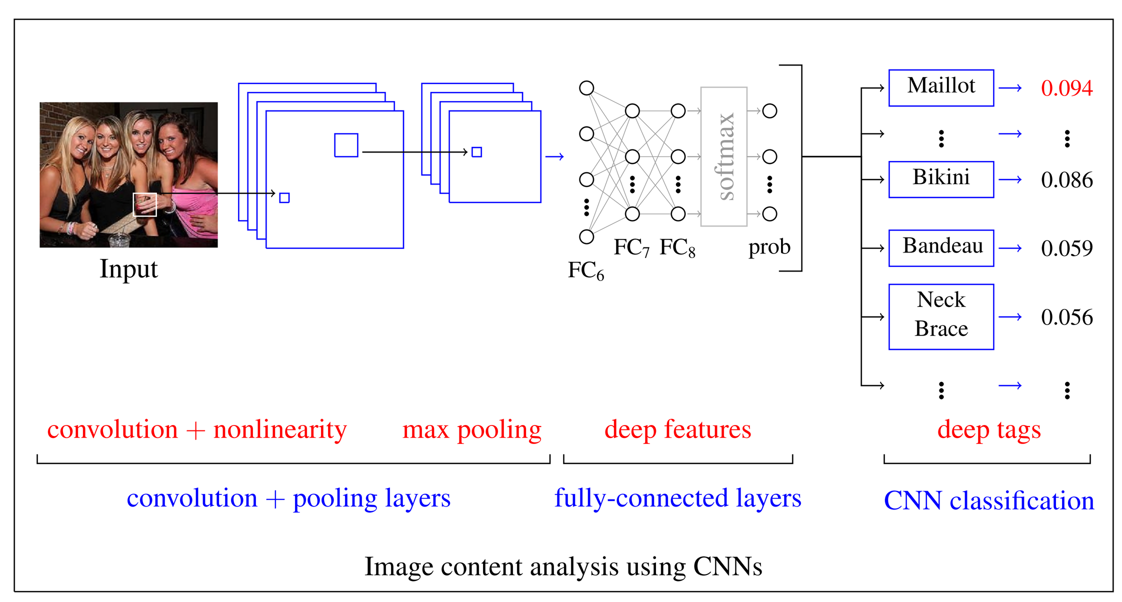


Figure: Proposed approach - Feature Extraction (Deep Features and Deep Tags): CNNs are used to extract deep visual features and deep image tags for input images.

Proposed Approach: Feature Classification

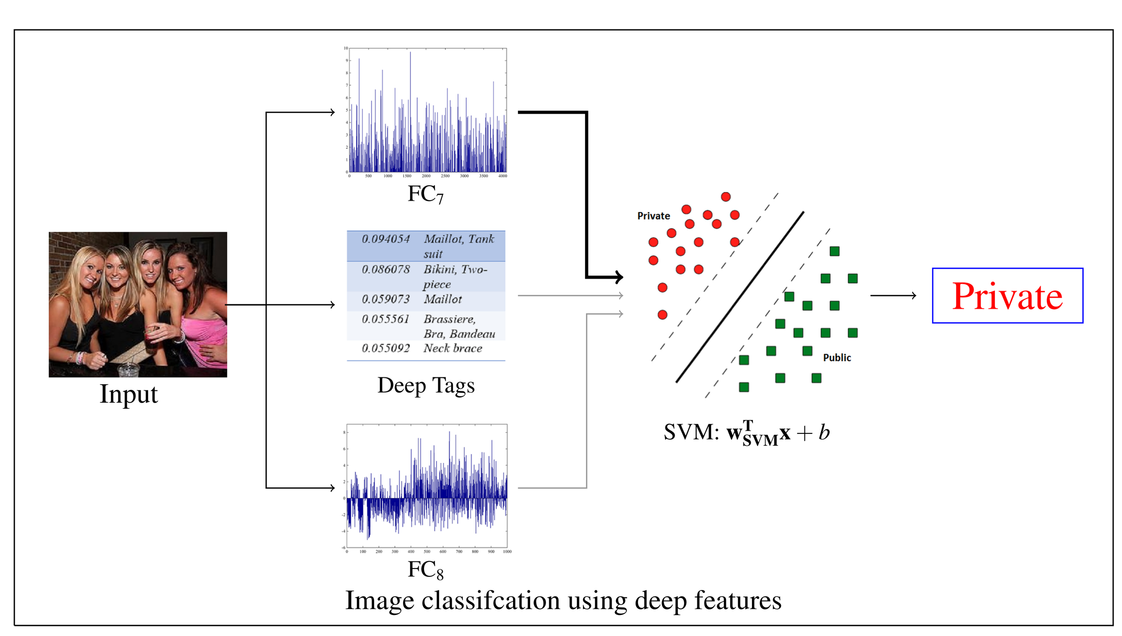


Figure: Proposed approach - Feature Classification (Deep Features and Deep Tags): The features from the fully-connected (fc) layers and deep tags are used to predict the class of an image as public or private using SVM.

Deep Tags vs. User Tags

Figure: Deep Tags vs. User Tags. For deep tags, we consider top $K = 5$ object labels as tags.

Important Links

- Extended Abstract: `http://www.cse.unt.edu/~ccaragea/posters/aaai16.pdf`
- Dataset: `https://www.dropbox.com/s/ydfpu51dec51krh/idsAndPrivacy.csv?dl=0`
- Full-length Paper: `http://arxiv.org/abs/1510.08583`

Experiments and Results

How do deep visual features compare with other existing state-of-the-art methods SIFT and GIST?

Features	Accuracy	F1-Measure	Precision	Recall
Test (*PiCalert*$_{783}$)				
FC_7	81.23%	0.805	0.804	0.812
FC_8	**82.63%**	**0.823**	**0.822**	**0.826**
SIFT + GIST	72.67%	0.661	0.672	0.727

Table: Performance of SVM using deep features in comparison with the combination of SIFT and GIST, on **Test**. For SIFT, we constructed a vocabulary of 128 visual words. For GIST, we considered feature vector of 512 (16 averaged value ×32 gabor filters) length.

How do tag features perform on the privacy prediction task?

Features	Accuracy	F1-Measure	Precision	Recall
Test (*PiCalert*$_{783}$)				
User Tags	79.82%	0.782	0.786	0.798
Deep Tags	80.59%	0.801	0.799	0.806
User + Deep Tags	**83.14%**	**0.827**	**0.826**	**0.831**

Table: Results obtained on tag features. For deep tags, we consider top $K = 10$ object labels as tags.

How do deep features perform for private class compared to SIFT and GIST?

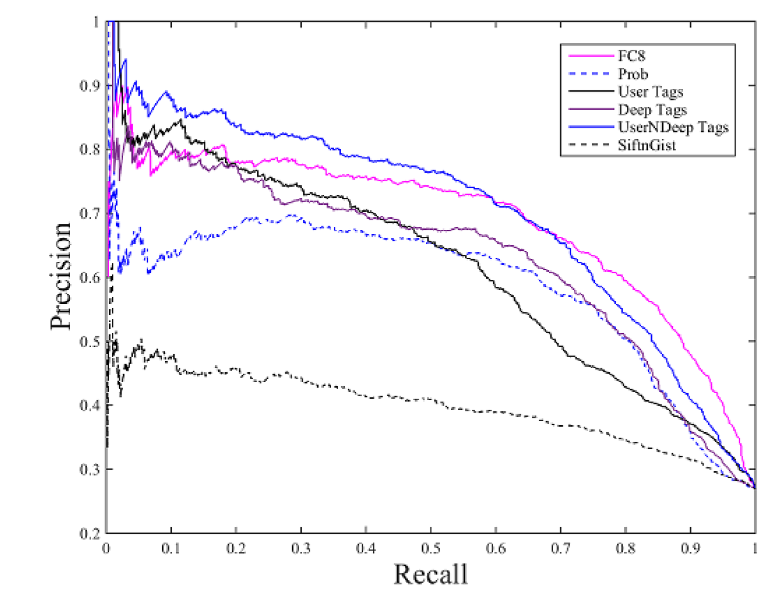
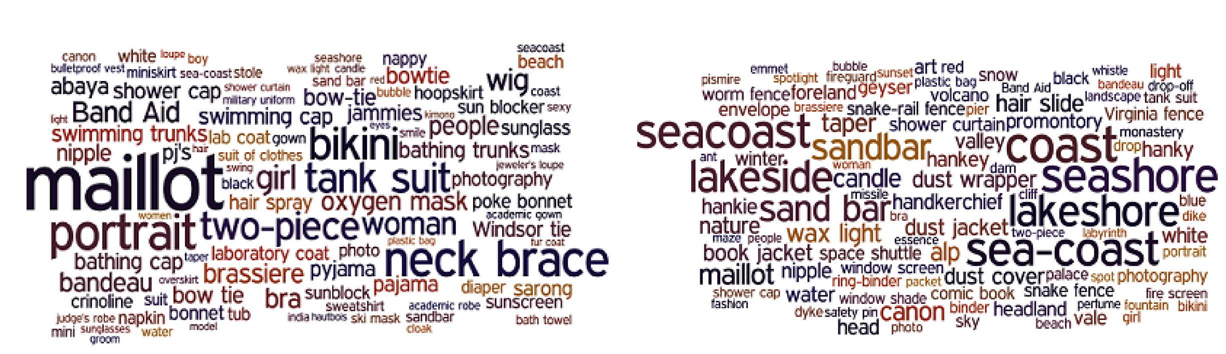


Figure: Precision and recall curves of different features for private class.

Which user tags and deep tags are useful for privacy prediction task?

Rank 1-5	Rank 6-10	Rank 11-15
Portrait	Maillot	Bathing Cap
Neck Brace	Wig	Swimming Cap
Two-piece	Bow-tie	Oxygen Mask
Bikini	**Girl**	Swimming Trunks
Tank Suit	**Woman**	Band Aid

Table: Tags with high information gain calculated using 5-fold cross validation. Bold words indicate user provided tags, while the others are deep tags.



(a) Private (b) Public

Figure: Tag clouds contains top 100 high frequency tags with respect to private and public images. High frequency tags represents frequently occurring tags to describe images for a particular privacy setting.

Conclusions

- We proposed an approach based on deep features and tags for privacy prediction.
- Deep features are explored at various network layers and also used top layer (probability) for auto-annotation mechanism.
- We examined user annotated tags and deep tag features.
- Our experiments shows that proposed method outperforms all baseline approaches.
- Future directions.
  - Refine user tags by using keyword extraction mechanism.
  - Combine visual features and tag features to get improved results.

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Acknowledgements: This research is supported by a grant from NSF to Cornelia Caragea. We thank Adrian Silvescu and Raymond J. Mooney for helpful discussions. WWW: http://www.cse.unt.edu/~ccaragea