数据隐私方法伦理和实践
Methodology, Ethics and Practice of Data Privacy

6. 隐私检测
Privacy Detection

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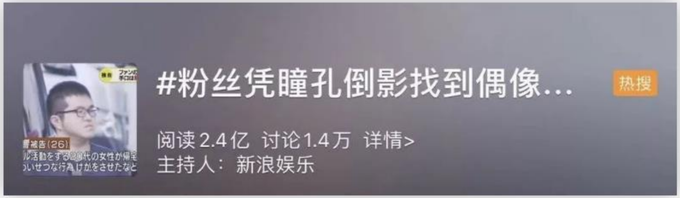
Privacy risks is horrible but hard to detect.

Ignored details



Additional metadata

Content correlation

Aim to answer:

Is the data private?

&

Why?

Consensus of Privacy Detection

Privacy Related Factors $\xrightarrow{\text{Lead to}}$ Private Data

Could be :

- Metadata
- Specific parts of data
- Specific connections between parts of data
- …

Methods should be effective and interpretable

Overview of Privacy Detection Techniques

» User-defined methods

- Define private related factors by user

Privacy Related Factors → (Lead to) → Private Data

Define factors by user → Detect private data

» Machine Learning Based Methods

- Discover private related factors in a data driven way

Privacy Related Factors → (Lead to) → Private Data

Discover Potential factors by data analysis → Detect private data

Privacy Detection Techniques

Take image, a representative modal of unstructured data, as an example:

- User-defined Methods
  - Image-level user survey
  - Object-level user survey

- Machine Learning Based Method
  - Content sensitiveness
  - Multimodal fusion

Privacy Detection Techniques

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User-defined Methods – Image Level

- PicAlert!: A System for Privacy-Aware Image Classification and Retrieval [1]
    - Aim to search related images with key word/Predict privacy label of a new image
    - Main work
        - Label data manually (image-level)
        - Extract features and train a classifier

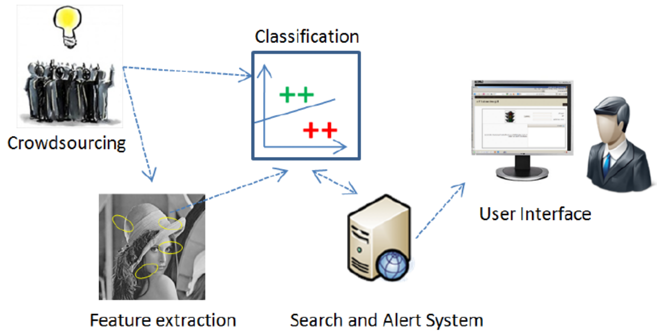

Figure 1: System architecture overview.

User-defined Methods – Image Level

- An image-level privacy dataset
  - Obtain image privacy dataset with label by crowdsourcing
    - 37535 images from Flickr
    - 81 judgers between 10 and 59 years old
    - Each picture was labeled private or public if at least 75% of the judges were of the same opinion.
    - 4701 images are labeled as private; 27405 images are labeled as public; remainder are labeled as undecidable
- Features and Classifier
  - Features: SIFT
  - Classifier: SVM

User-defined Methods – Image Level

- An example of search results

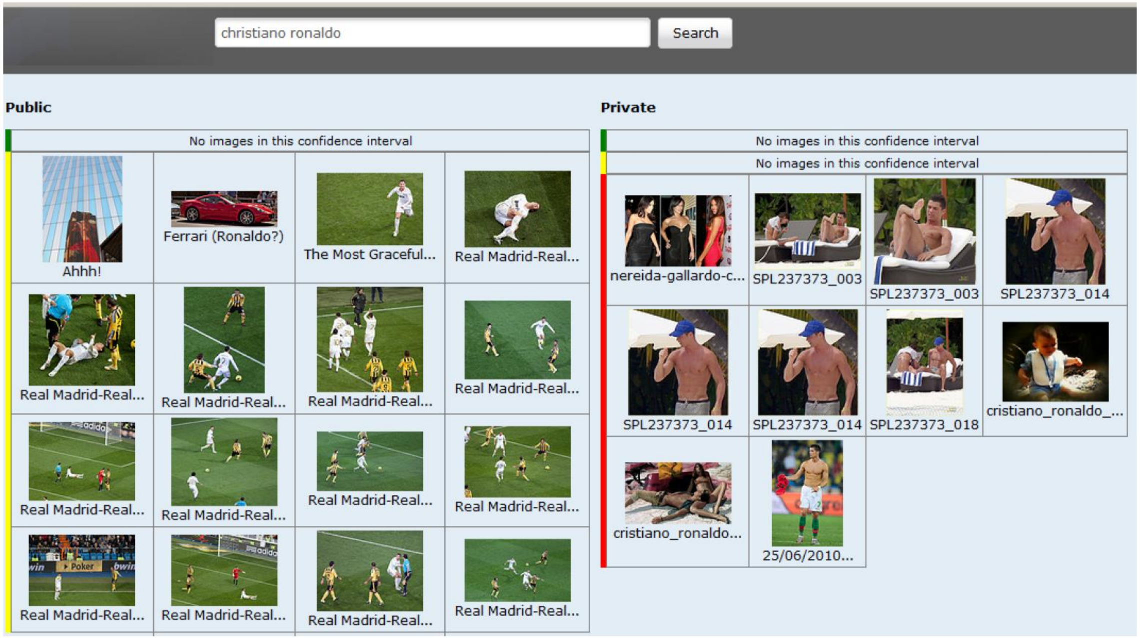

Figure 3: Private and public search results for the query "cristiano ronaldo" (June 06 2012).

Privacy Detection Techniques

Take image, a representative modal of unstructured data, as an example:

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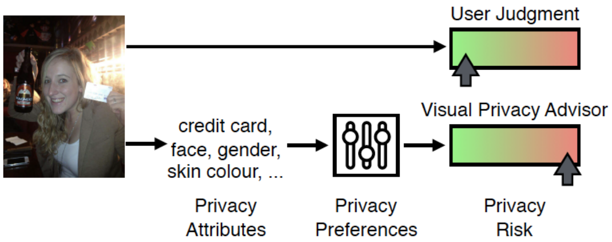
User-defined Methods – Object Level

- Towards a visual privacy advisor: Understanding and predicting privacy risks in images [2]
  - Aim to predict risk
  - Main work
    - Identify privacy attributes manually from multiple sources
      - EU Data Protection Directive 95/46/EC
      - US Privacy Act of 1974
      - Relevant attributes on Twitter/Flickr/Reddit/…
    - Label data manually (object-level)
    - Conduct user study to discover user privacy preference
    - Attribute detection & privacy risk prediction



User-defined Methods – Object Level

- The Visual Privacy(VISPR) Dataset: An object-level privacy dataset
  - Data Collection:
    - 22167 images from Flickr
  - Compilation of 68 privacy attributes from multiple sources:
    - EU Data Protection Directive 95/46/EC
    - US Privacy Act
    - The rules on prohibiting sharing personal information on various social networking websites (e.g., Twitter, Reddit, Flickr)
  - Data Labeling:
    - 68 privacy attributes of Images are labeled

User-defined Methods – Object Level

- Label distribution of VISPR Dataset

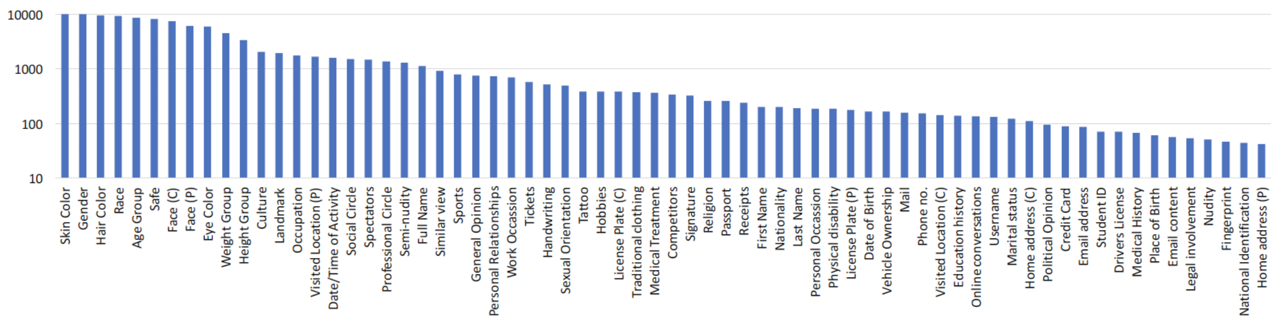
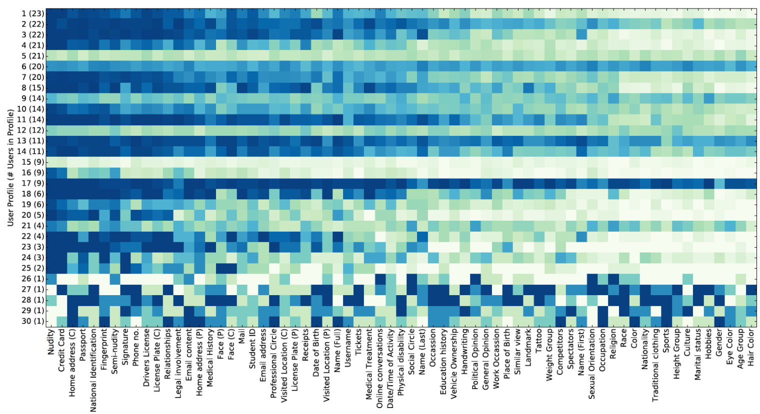


Figure 2: Label distribution in our dataset. Y-axis indicates the number of images.

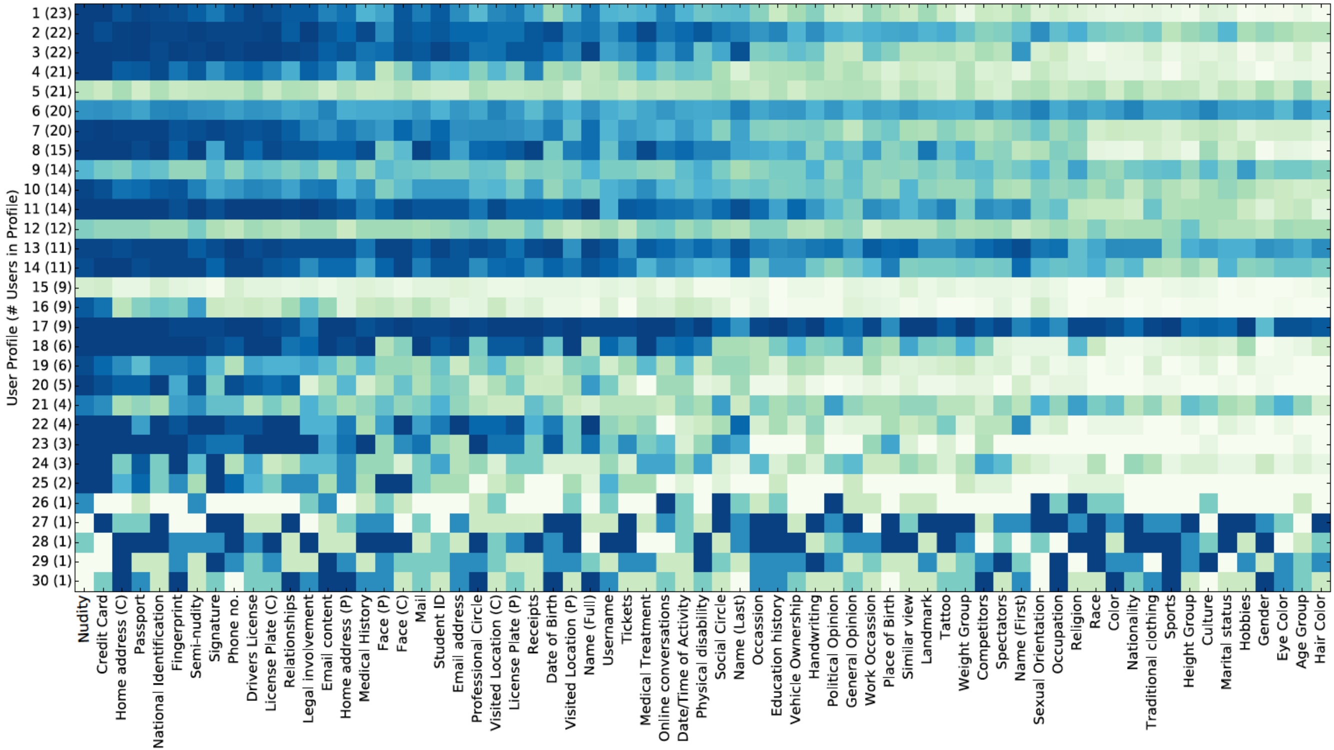
Images	22,167
Labels	115,742
Avg Labels/Image	5.22
Max Images/Label	10,460
Min Images/Label	44

User-defined Methods – Object Level

- User Study
  - 30 user profiles
    - 305 unique AMT workers
    - Workers rate images and 68 private attributes in VISPR independently
    - Higher score indicate greater sensitivity to privacy



User-defined Methods – Object Level



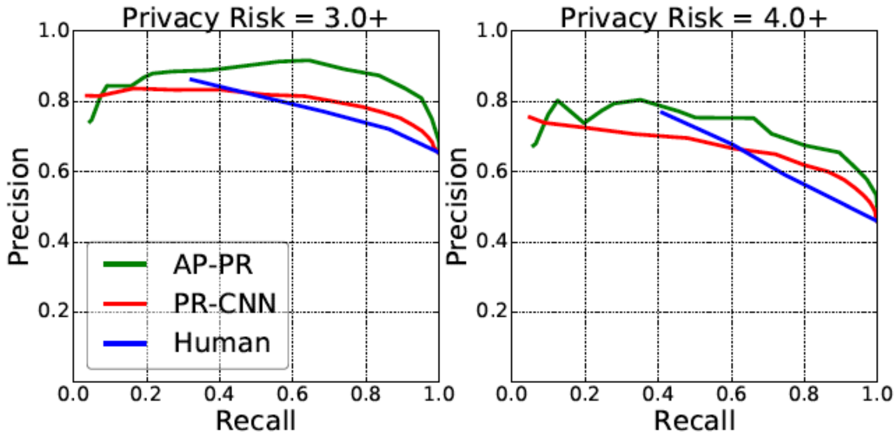
User-defined Methods – Object Level

- Privacy risk prediction
  - Identify user profile
  - Attribute detection
  - Privacy risk prediction

Definition 1. *Privacy Risk Score.* For some image $\boldsymbol{x}$, attributes $\boldsymbol{y} \in [0,1]^A$ and user preference $\boldsymbol{u} \in [0,5]^A$, the privacy risk score of image $\boldsymbol{x}$ containing attributes $\boldsymbol{y}$ on user $\boldsymbol{u}$ is $\max_a \boldsymbol{y}_a \boldsymbol{u}_a$

User-defined Methods – Object Level

- An interesting finding in VISPR
  - Users often fail to enforce their privacy preferences when sharing images online.



Privacy Detection Techniques

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ML Based Methods – Content Sensitiveness

- iprivacy: Image privacy protection by identifying sensitive objects via deep multi-task learning[3]
  - Aim to predict privacy label of image
  - Main work:
    - Align privacy setting(Privacy/Public/Shared with acquaintance/...) to object classes
    - Detect private object classes via DNN
      - Use DNN to detect classes
      - Use top-down hierarchical clustering to improve efficiency

ML Based Methods – Content Sensitiveness

- Automatic object-privacy alignment

Feature Extraction →	Clustering →	Privacy alignment →	Refinement
Deep CNN	K-means	Frequency of occurrence	Random walk

ML Based Methods – Content Sensitiveness

Feature Extraction → Clustering → Privacy alignment → Refinement

Deep CNN | K-means | Frequency of occurrence | Random walk

- Extract feature by DNN
  - Full set of 1000 object classes
  - 1000-dimensional sparse representation vector *X*
- Clustering images according to KI
  - Number of clusters K is a parameter

$$\kappa_I(X_i, X_j) = \sum_{l=1}^{1000} \delta(X_i^l, X_j^l) \qquad \delta(X_i^l, X_j^l) = \begin{cases} 1, & if \quad X_i^l = X_j^l = 1; \\ 0, & otherwise \end{cases}$$

ML Based Methods – Content Sensitiveness

Feature Extraction	→	Clustering	→	Privacy alignment	→	Refinement
Deep CNN		K-means		Frequency of occurrence		Random walk

» Align privacy relevance score

- For each cluster:
  - Calculate relevance score between each object class and each privacy setting

$$\gamma(C_i, t) = \frac{\| \Psi(C_i, t) \|}{\| \Psi(C, P) \|} \quad t \in P$$

  - Align the privacy setting with highest γ to the object class

ML Based Methods – Content Sensitiveness

Feature Extraction	→	Clustering	→	Privacy alignment	→	Refinement
Deep CNN		K-means		Frequency of occurrence		Random walk

» Refine privacy relevance score

- Construct co-occurrence network
  - The object classes, which have large values of co-occurrences $\phi(.,.)$, are connected to form an object cooccurrence network.

$$\phi(C_i, C_j) = \rho(C_i, C_j) \log \frac{\rho(C_i, C_j)}{\rho(C_i) + \rho(C_j)}$$

$$\rho(C_i, C_j) = \frac{N(C_i, C_j)}{N}, \quad \rho(C_i) = \frac{N(C_i)}{N}, \quad \rho(C_j) = \frac{N(C_j)}{N}$$

ML Based Methods – Content Sensitiveness

- Refine privacy relevance score on co-occurrence network by random walk
  - Update score iteratively:

For each t, let $\rho_0(C_i, t) = \gamma(C_i, t)$

$$\rho_k(C_i, t) = \theta \sum_{C_j \in \Omega_{C_i}} \rho_{k-1}(C_i, t)\psi_{ij} + (1-\theta)\gamma(C_i, t)$$

where, $\psi_{ij} = \dfrac{\phi(C_i, C_j)}{\sum_{C_k \in \Omega_{C_i}} \phi(C_i, C_k)}$

- Align privacy setting t with biggest ρ to Ci
  - 268 object classes is identified as privacy-sensitive classes

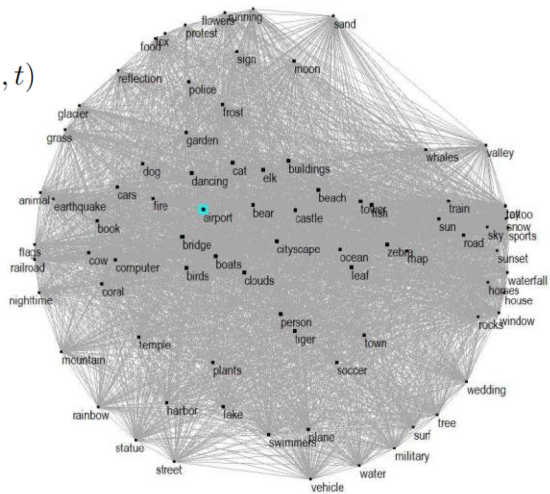

Fig. 6. **A small part of our object co-occurrence network.**

ML Based Methods – Content Sensitiveness

- Results of privacy alignment
  - Obtain 268 privacy-sensitive object classes from 1000 classes

TABLE I
The short list of privacy-sensitive object classes identif ed by this work.

Categories	Privacy-Sensitive Object Classes
Human Beings	portrait, people in birthday party, human body, human hair, human face, human eye, human neck, people in award, mannequin modeling, customer, $\cdots$
Family	baby, children, relatives/family, friend, husband, wife, parents, brother, sister, cousin, kids at play, african american, couple, $\cdots$
Woman	girl, explicit women, female surf ng, $\cdots$
Ethic	erotic, $\cdots$
House	home, bedroom, restroom, indoor, kitchen, $\cdots$
Clothes	suit, bikini, maillot, $\cdots$
Activity	drinking, wedding, swimming, bathing, working boys, sitting on boys, f shing, birthday parties, travel, vacations, fun summer vacation, $\cdots$
Work Lab	science lab, laptop, computer, personal , $\cdots$

ML Based Methods – Content Sensitiveness

- Results of privacy alignment
  - Obtain 268 privacy-sensitive object classes from 1000 classes

TABLE II

The short list of public object classes identif ed by this work.

Categories	Public Object Classes
Nature & Scenery	mountain, island, rock, sand, sea, coast, lake, river, sunset, sky, landscape, lakeside, sandbar, beach, cartoon, f re, ice, water, fashion, $\cdots$
Animal	pets, dog, cat, bird, wild animals, f sh, $\cdots$
Plant	f ower, tree, asian f oral, $\cdots$
Season	winter, sprint, summer, autumn, $\cdots$
Transportation	road, traff c, boat, car, $\cdots$
Building	House outside, garden, bridge,shopping center,park, bank, $\cdots$
Planet	moon, sun, earth, $\cdots$
City Signs	New York, Washington, Beijing, $\cdots$

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ML Based Methods – Multimodal Fusion

» Dynamic Deep Multi-modal Fusion for Image Privacy Prediction[4]

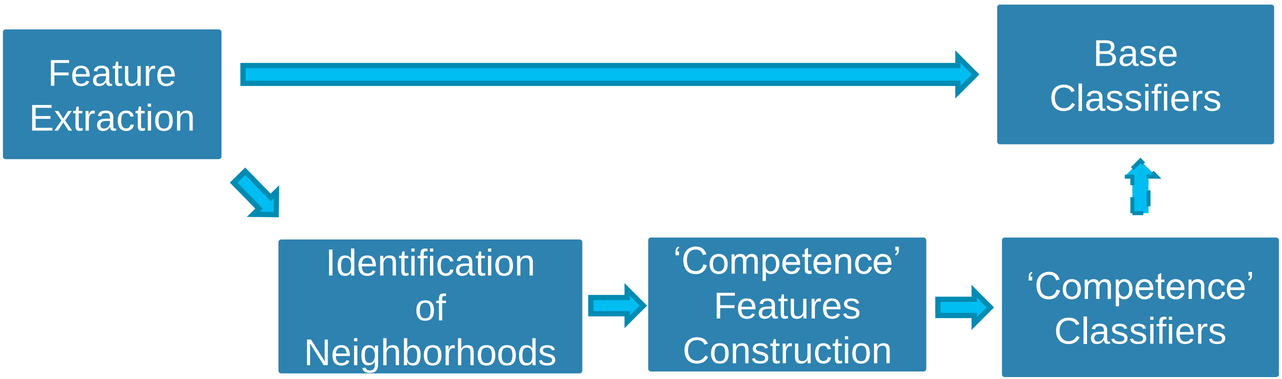
- Both image content, e.g. scene and object, and tags affect image privacy.
- Different images have different privacy factors

Single modality is correct			Multiple modalities is correct		
Image	Tags	Base classifiers	Image	Tags	Base classifiers
 (a)	bed, studio dining table speakers, music	**scene: 0.62** object: 0.5 tags: 0.29	 (d)	girl, baby indoor, people canon	scene: 0.49 **object: 0.87** **tags: 0.97**
 (b)	birthday night party, life	scene: 0.57 **object: 0.78** tags: 0.39	 (e)	people, party awesome, tea bed, blanket	**scene: 0.92** object: 0.38 **tags: 0.7**
 (c)	toeic, native speaker, text document, pen	scene: 0.02 object: 0.15 **tags: 0.86**	 (f)	indoor, fun party people	**scene: 0.92** **object: 0.73** **tags: 0.77**

ML Based Methods – Multimodal Fusion

» Dynamic fusion of three base classifiers

- Three base classifiers: Object, Scene and Tag classifiers
- Train ‘competence’ classifiers respectively to control the fusion process of base classifiers.



ML Based Methods – Multimodal Fusion

Feature Extraction → Identification of Neighborhoods → ‘Competence’ Features Construction → ‘Competence’ Classifier Training

Features

- Three base features by CNN: Train 3 base classifiers on the corresponding modality feature sets
  Object (F^o): 1000 dimension
  Scene (F^s): 365 dimension
  Image Tags (F^t): 265 dimension
- Combination feature: Using in ‘Neighoods identification’
  Object + Scene + Tag (F^{ost}): $f^{cat}(F^o, F^s, F^t)$
- Privacy profile feature: Using in ‘Neighoods identification’
  $$\overline{T} = \bigcup_{B_i \in \mathcal{B}} \{P(Y_T = private|T, B_i), P(Y_T = public|T, B_i)\}$$

ML Based Methods – Multimodal Fusion

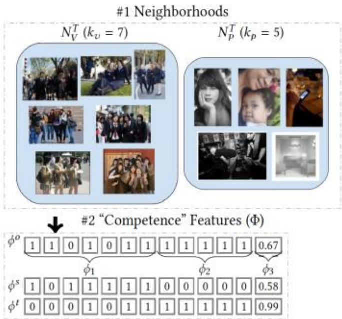
Feature Extraction → Identification of Neighborhoods → ‘Competence’ Features Construction → ‘Competence’ Classifier Training

Identification of Neighborhoods

- Find neighbors according to F^{ost} and $\overline{T}$ by cosine similarity.

‘Competence’ Features Construction

- $\phi^{o}, \phi^{s}, \phi^{t}$ are used to train corresponding competence classifiers
- Each ϕ is consist of three parts:
  - ϕ^{1} is the prediction results of Neighbors N_V^T by current base classifier
  - ϕ^{2} is the prediction results of Neighbors N_P^T by current base classifier
  - ϕ^{3} is the prediction results of input Image by current base classifier



ML Based Methods – Multimodal Fusion

Feature Extraction → Identification of Neighborhoods → ‘Competence’ Features Construction → ‘Competence’ Classifier Training

‘Competence’ Classifier Training

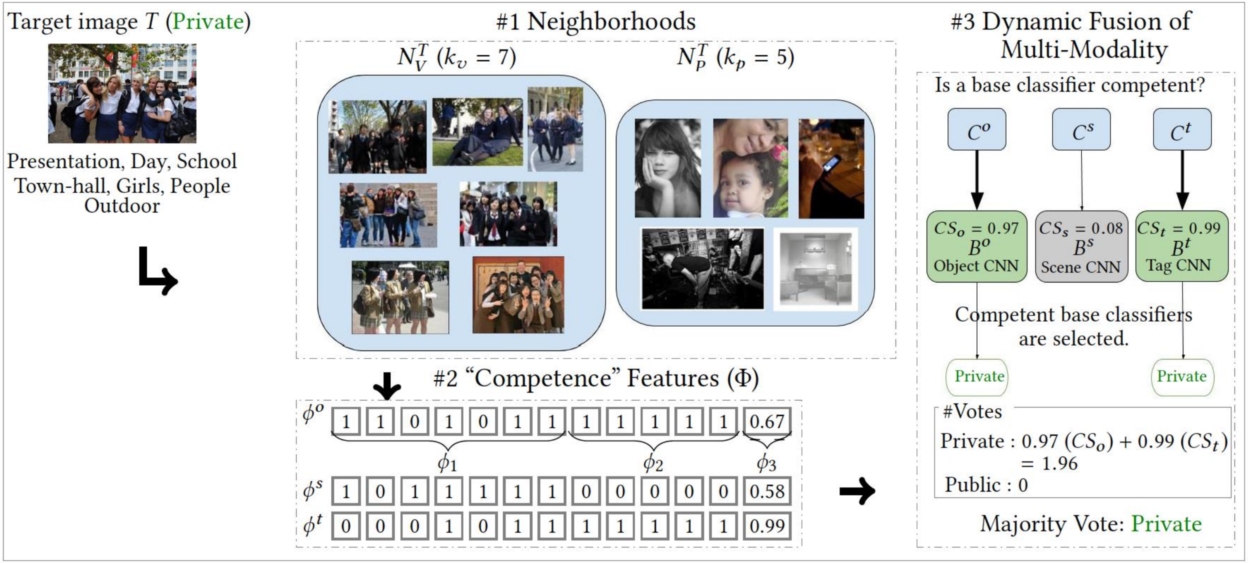
- Three competence classifiers $C = \{C^o, C^s, C^t\}$
- To train “competence” classifiers $C_i \in C$, we consider label Li = 1 if base classifier $B_i \in B$ predicts the correct privacy of a target image, otherwise 0.

Dynamic Fusion

- Dynamic voting: Dynamically determine the subset of most competent base classifiers
- Thresholding: If the competence score is greater than 0.5, then base classifier B_i is identified as competent to predict the privacy of target image
- The competence score is used as weight in final fusion

ML Based Methods – Multimodal Fusion

» An illustration of the proposed approach



ML Based Methods – Multimodal Fusion

Experiment Results

- Dataset is PicAlert

Features	Private			Public			Overall			
	Precision	Recall	F1-score	Precision	Recall	F1-score	Accuracy (%)	Precision	Recall	F1-score
DMFP	0.752	**0.627**	**0.684**	**0.891**	0.936	**0.913**	**86.36**	**0.856**	**0.859**	**0.856**
"Competence" Features										
DMFP−ϕ_1	0.777	0.553	0.646	0.874	0.951	0.911	85.74	0.849	0.852	0.844
DMFP−ϕ_2	0.74	0.565	0.641	0.875	0.939	0.906	85.11	0.842	0.846	0.84
DMFP−ϕ_3	0.752	0.627	0.683	0.891	0.936	0.913	86.35	0.856	0.859	0.856

Table 3: Evaluation of dynamic multi-modal fusion for privacy prediction (DMFP).

Model	 (a)	 (b)	 (c)	 (d)
DMFP	✓	✓	✓	✗
Object	✗	✓	✓	✗
Scene	✓	✗	✓	✗
Tags	✓	✓	✗	✗

Figure 4: Predictions for private images.

Reference

- [1] Zerr, Sergej, Stefan Siersdorfer, and Jonathon Hare. "PicAlert! a system for privacy-aware image classification and retrieval." Proceedings of the 21st ACM international conference on Information and knowledge management. 2012.
- [2] Orekondy, Tribhuvanesh, Bernt Schiele, and Mario Fritz. "Towards a visual privacy advisor: Understanding and predicting privacy risks in images." Proceedings of the IEEE International Conference on Computer Vision. 2017.
- [3]Yu, Jun, et al. "iPrivacy: image privacy protection by identifying sensitive objects via deep multi-task learning." IEEE Transactions on Information Forensics and Security 12.5 (2016): 1005-1016.
- [4] Tonge, Ashwini, and Cornelia Caragea. "Dynamic deep multi-modal fusion for image privacy prediction." The World Wide Web Conference. 2019.

Exercise

Exercise

- Ex.1
  - Read a paper about Privacy detection and write a report.
- Ex.2
  - Reproduce the deep random walk in [3].
- Ex.3
  - *Reproduce the dynamic fusion algorithm in [4]

THANKS!
Any questions?

You can find me at:

- @username
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