Privacy score

Privacy

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Outline

Outline

Outline

Outline

Behavioral

Privacy Detective: Detecting Private Information and Collective Privacy Behavior in a Large Social Network [1]

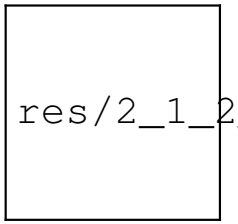


Figure 1: User privacy score-1

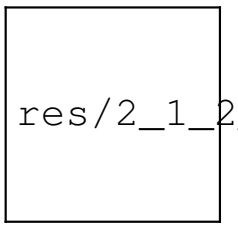


Figure 2: User privacy score-2

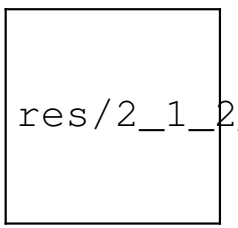


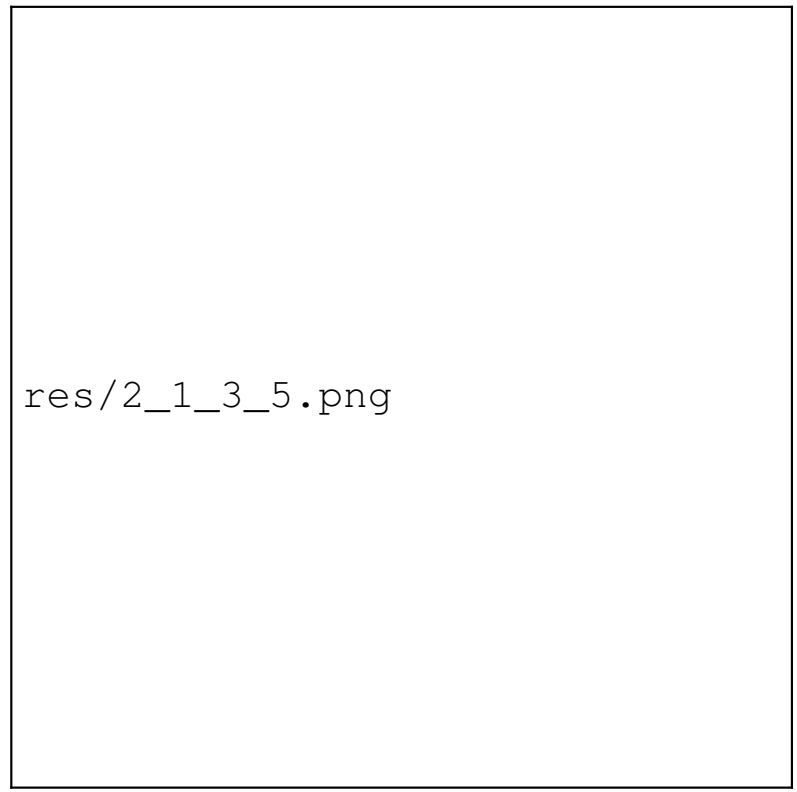
Figure 3: User privacy score-3

- Content based features (Timelines)
- Amazon mechanical turk annotations (labeling)
  - Annotate the publicly available data which is used for calculating the privacy scores.
- 3-class supervised learning
  - Timelines are classified with privacy scores by using AdaBoost with Naive Bayes classifier.
- Study the correlation between Users Privacy Score and:
  - Users Friends Privacy Score (fig 1, 2, 3)
    - R value is 0.41, and a two-tailed P value is 0.005.
  - Mentioned (CC) Users Privacy Score
    - R value is 0.37 and a two-tailed P value is 0.01.
    - Users prefer to follow users that have similar privacy revealing habits.
  - Number of Friends
    - There is no statistically significant correlation between a users privacy score and the number of friends.

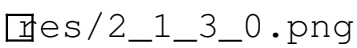
Behavioral

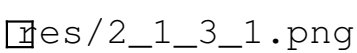
Detecting and resolving privacy conflicts for collaborative data sharing in online social networks [2]

- Input
  - Number of privacy conflicts $controllers_{ut}(i)$
    - number of the untrusting controllers
  - General privacy concern of an untrusting controller pc_j
  - Sensitivity of the data item sl_j
  - Visibility of the data item
  - Trust of an accessor tl_k (MTA)

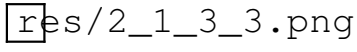


- Measuring Privacy Risk:

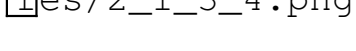




- Measuring Sharing Loss:

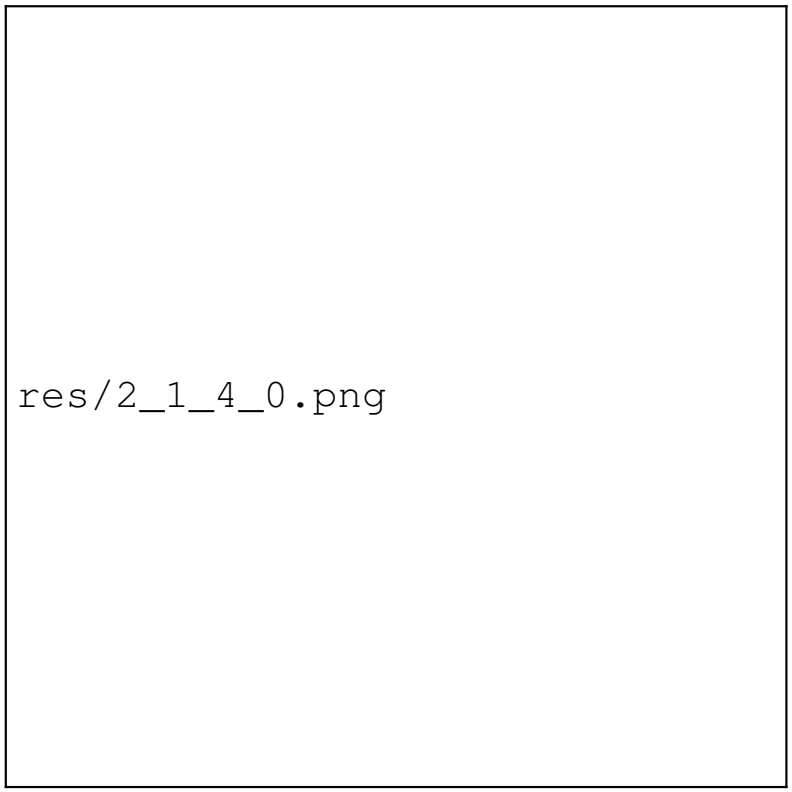


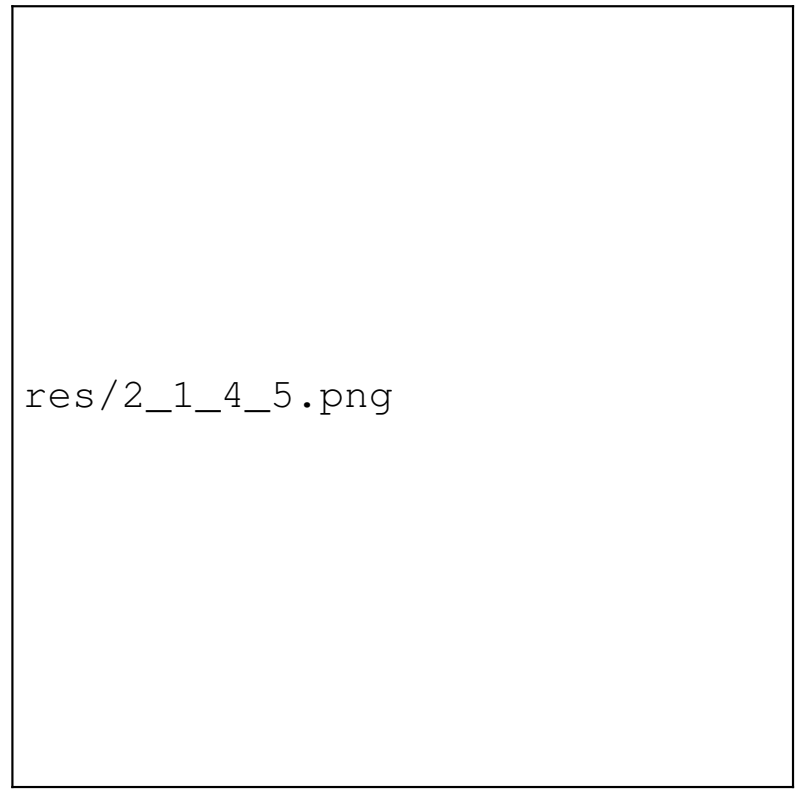
- Privacy Conflict Resolution on the Tradeoff between Privacy Protection and Data Sharing:



Trust Model

Computational Trust Model for Repeated Trust Games [3]





Behavioral

Styx: Privacy risk communication for the Android smartphone platform based on apps' data-access behavior patterns [**bal_styx_2015**]

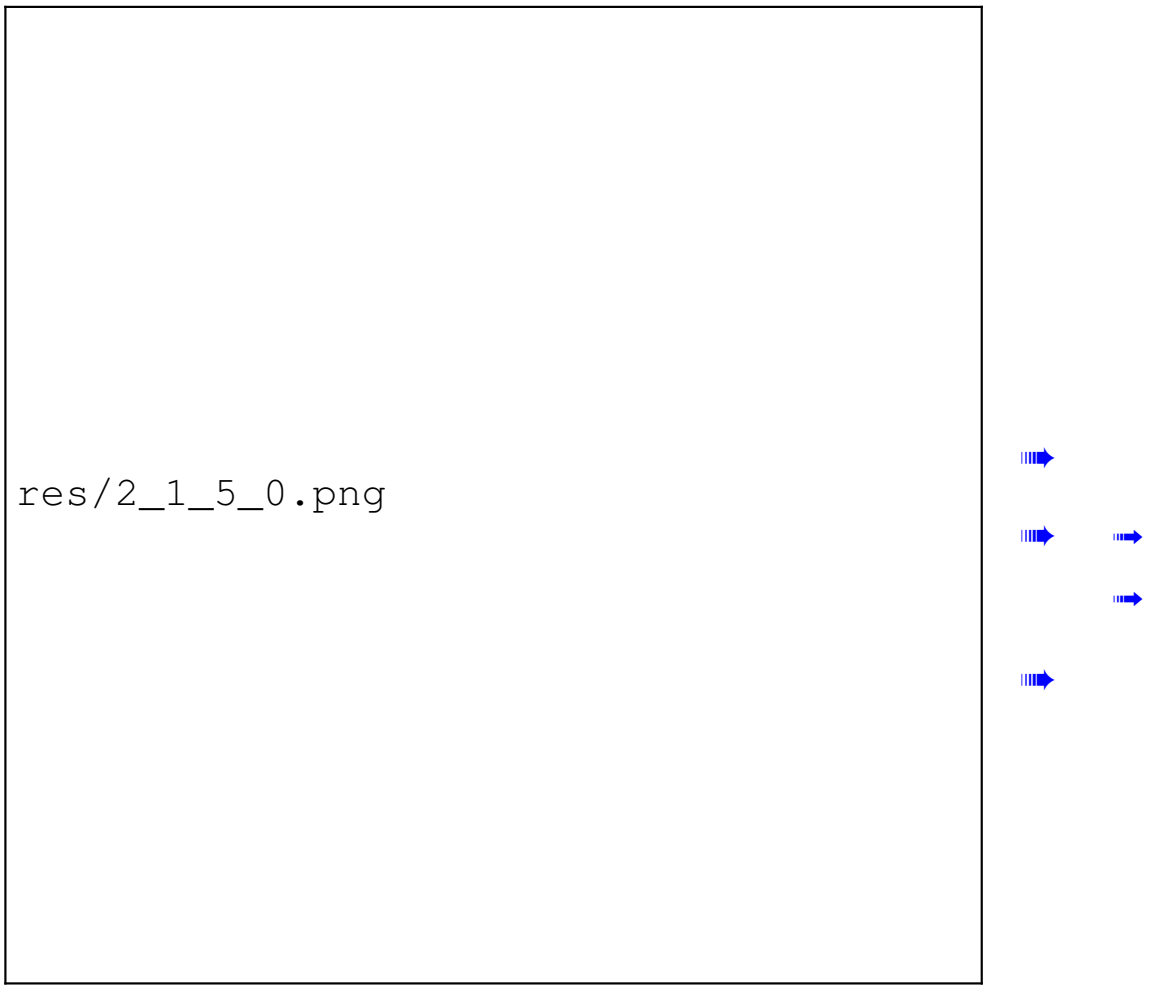
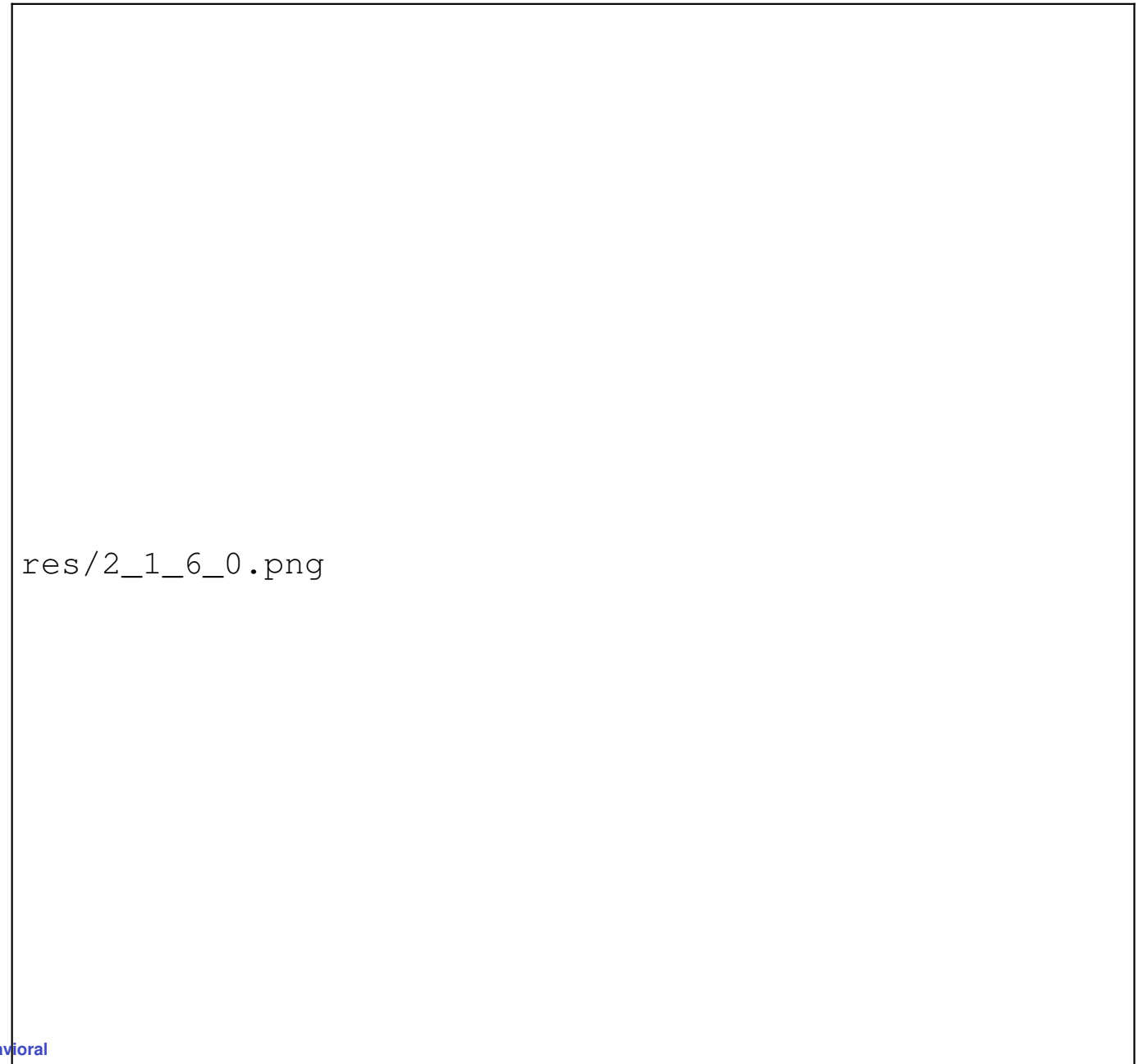


Figure 4: Cag.

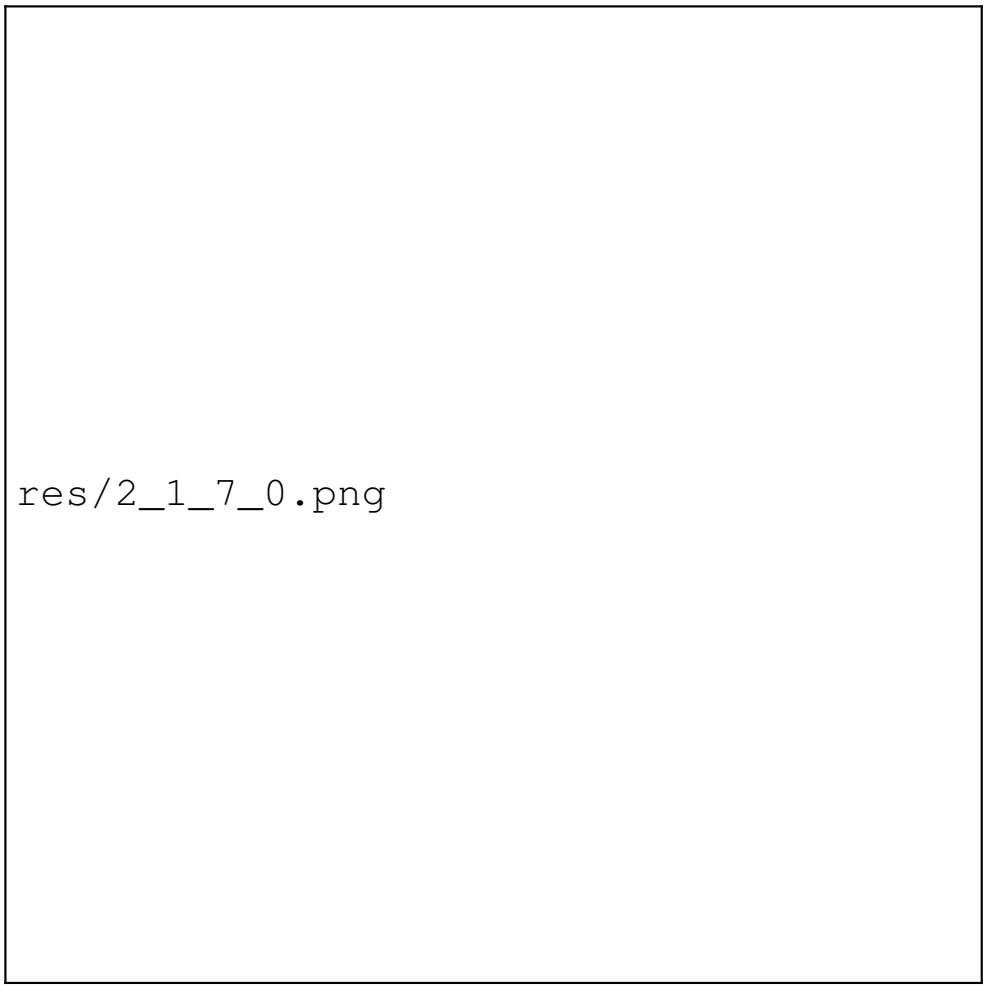
Behavioral

Exploring nuances of user privacy preferences on a platform for political participation [4]



Behavioral

Prometheus: User-controlled P2P Social Data Management for Socially-aware Applications [5]

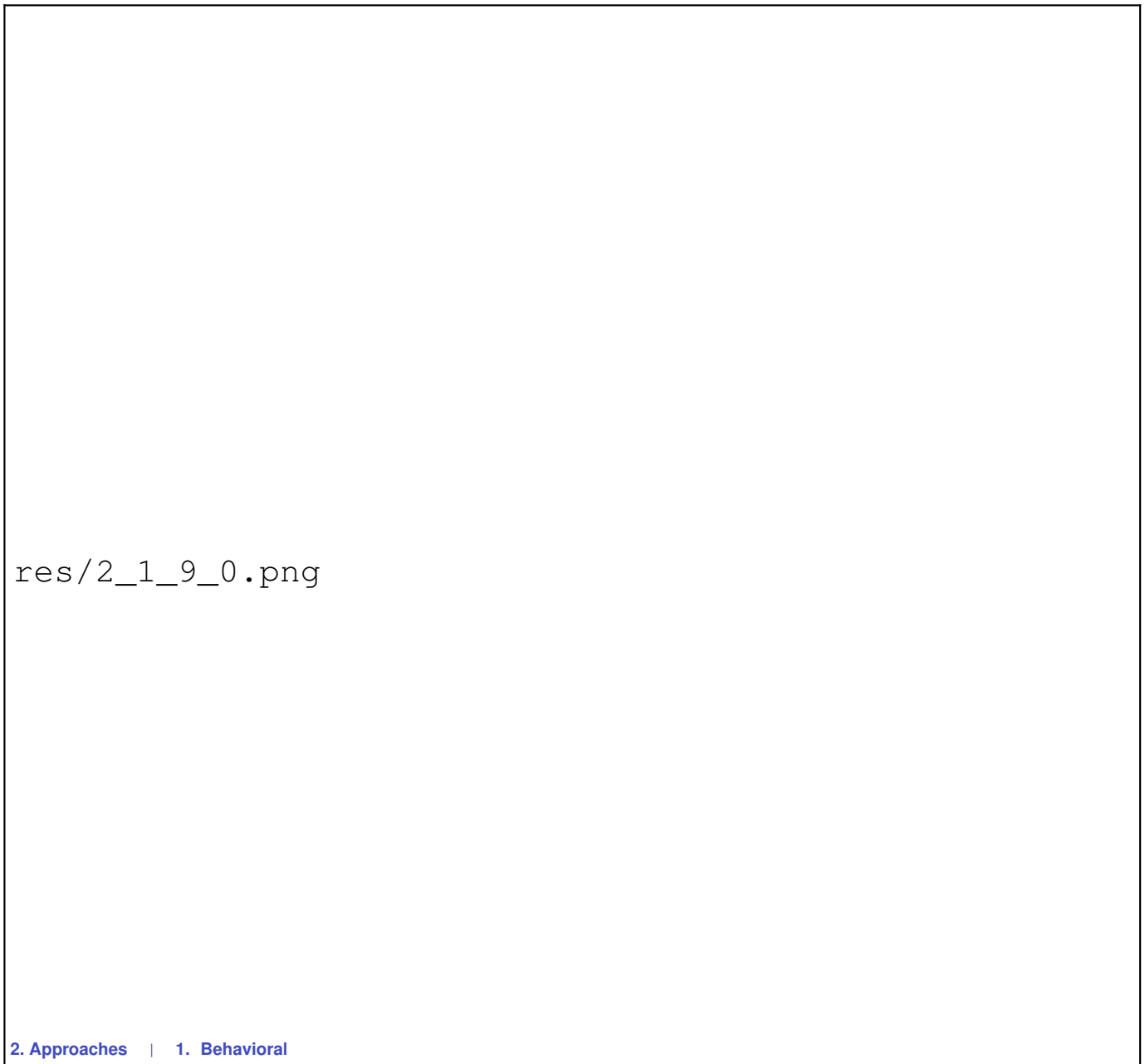


- Trusted Peer Group Management
  -
  -
  -

Figure 7: Geo-social Graph Representation

Behavioral

Computing Privacy Risk and Trustworthiness of Users in SNSs [6]

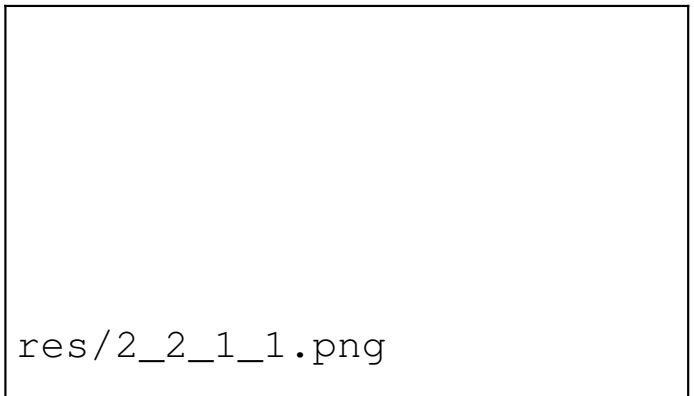


Outline

Social

A Study of Online Social Network Privacy Via the TAPE Framework [7]

Figure 10: Cag.



- Node Information Spreading (NISP)
  - How likely a friend will spread other's PI ?
- Methods
  - TAPE: The friend with the largest Birnbaum's measure is blocked.
    - Evaluate the sensitivity of a friend link
  - Friend Degree: The friend that has the largest degree is blocked.
    - Evaluate the importance of a friend link
  - V-Index: The friend that has the largest V-Index is blocked.
    - Evaluate privacy setting of a friend ...
  - Random: Random friends are blocked.
    - Privacy risk decrease as undesirable destination (NISP) blocked

- Privacy risk decrease as undesirable destination (NISP) blocked

- Link Information Spreading (LISP)
  - How likely a friend will be in the path of PI diffusion

Social

Algorithm to trade off between utility and privacy cost of online social search [8]

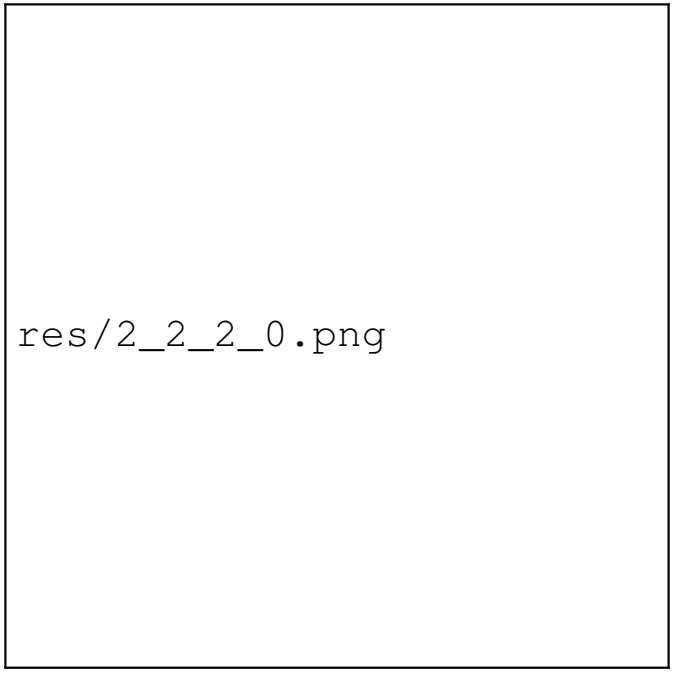


Figure 12: Cag.

- Input:
  - p: Probability of influence from u to v.
  - dv: Degree of the node v.
  - sv: Number of neighbors of v who are seeds.
  - tv: Number of neighbors of v who are seeds and experts
- Method:
  - Utility Degree Discount Algorithm:
    - If (expert) $d_{dv} = (1-p)^{sv}$ [1 + (dv - tv)]
    - Else $d_{dv} = (1-p)^{sv}$ (dv - tv)
  - Utility Privacy Cost Ratio Discount Algorithm:
    - If (expert) $d_{dv} = (1-p)^{sv}$ [1 + (dv - tv)] / (dv - sv)
    - Else $d_{dv} = (1-p)^{sv}$ (dv - tv) / (dv - sv)
- Output:
  - Privacy: Number of seeds activated (FP)
  - Utility: Number of expert activated (TP)

Social

Privacy scoring of social network users as a service [9]

- Input
  - l0 [0, 1] : Disposition to privacy:
    - Attitude of an user towards privacy of his information.
    - l0 = 0,1 : Lax privacy orientation
  - h0 [0, 1] : Disposition to communication:
    - Attitude of an user towards communication online.
    - h0 = 0.1 : User who is very communication oriented
  - Friend Attitude Calculator (FACT):
    - Pn: The friends position in the sorted trust list.
    - Cn: The percentage of total communication.
    - tx: Total number of friends.

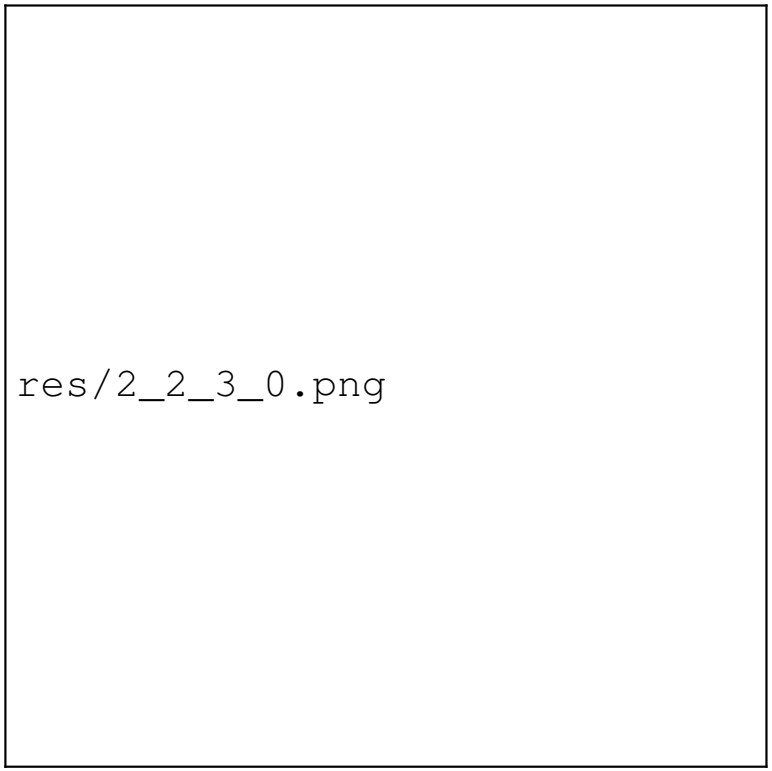
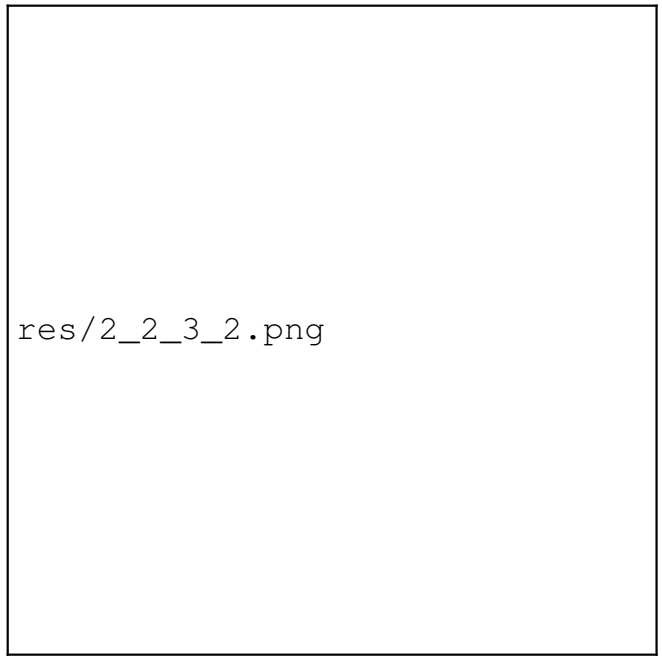


Figure 14: Experiment results with varying l0 and h0



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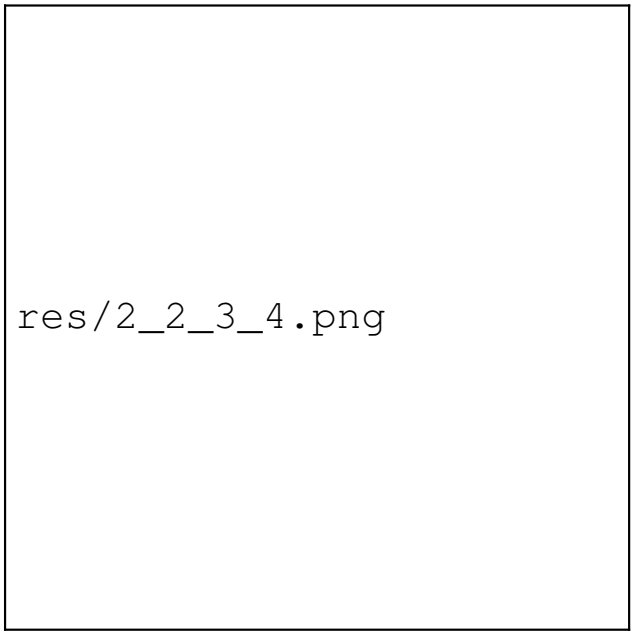
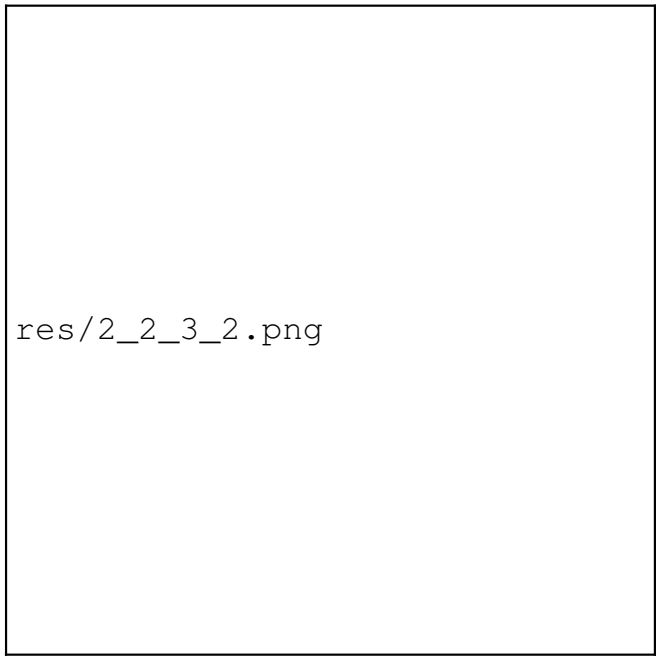


Figure 16: Experiment results with varying l0 and h0



Social

Privometer: Privacy protection in social networks [10]

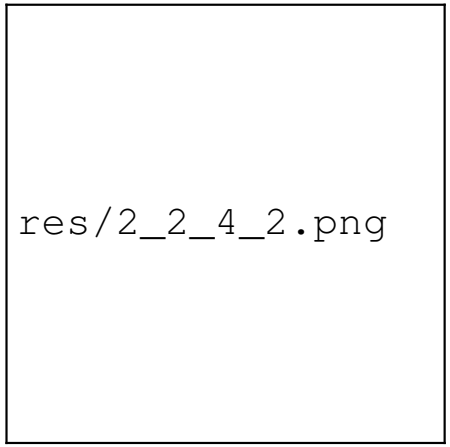
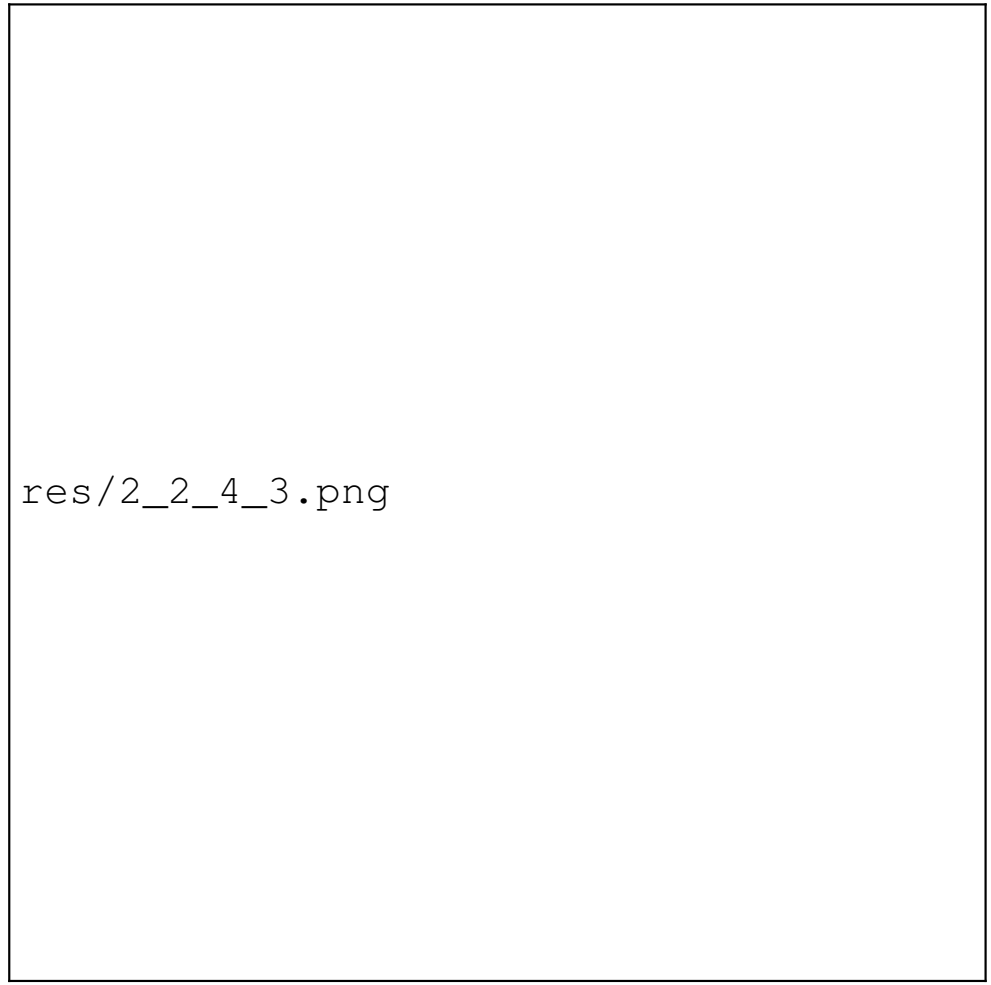
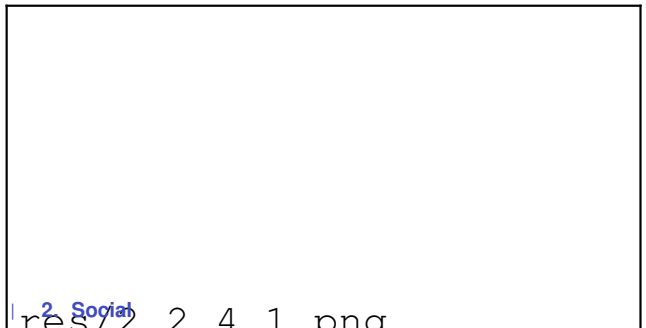


Figure 18: Information Visibility in User Profile





Social

Privacy impact assessment for online social networks [11]

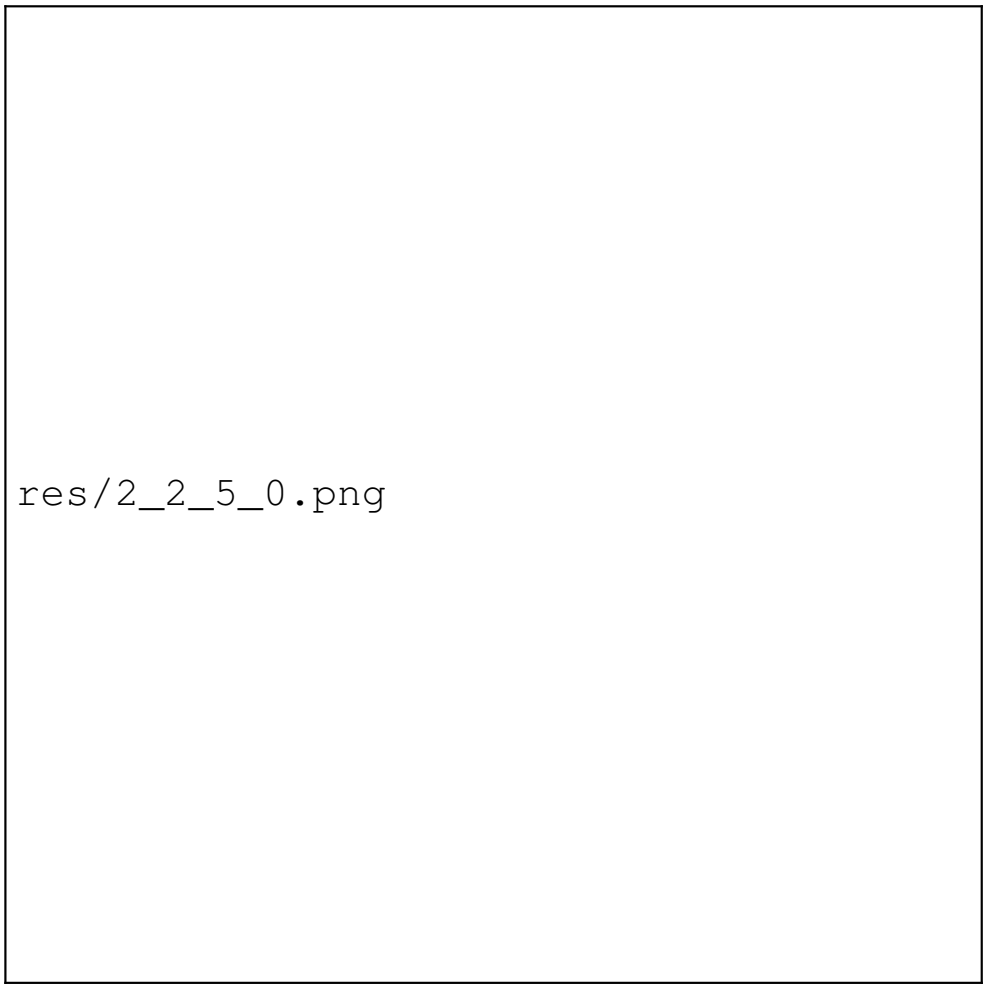


Figure 21: Data loss and Privacy Impact

- Direct Data Loss (Access control models)
  - I-BAC: Individual-Based Access Control
  - A-BAC: Authority-Based Access Control
  - T-BAC: Team-Based Access Control
    - R-BAC: Role-Based Access Control
    - Or-BAC: Organization-Based Access Control
    - Re-BAC: Relationship-Based Access Control
- Indirect Data Loss
  - Inference, aggregation, and de-anonymization.
- Potential Data Loss
  - Social engineering, phishing.

Social

Privacy-triggered communications in pervasive social networks [12]

- Input:
  - s: Device privacy (state)
  - b: Message privacy (action)
  - R: Reward
  - u: Stationary policy
- Method:
  - P_{ij} is the probability to transition from state si to sj at time t

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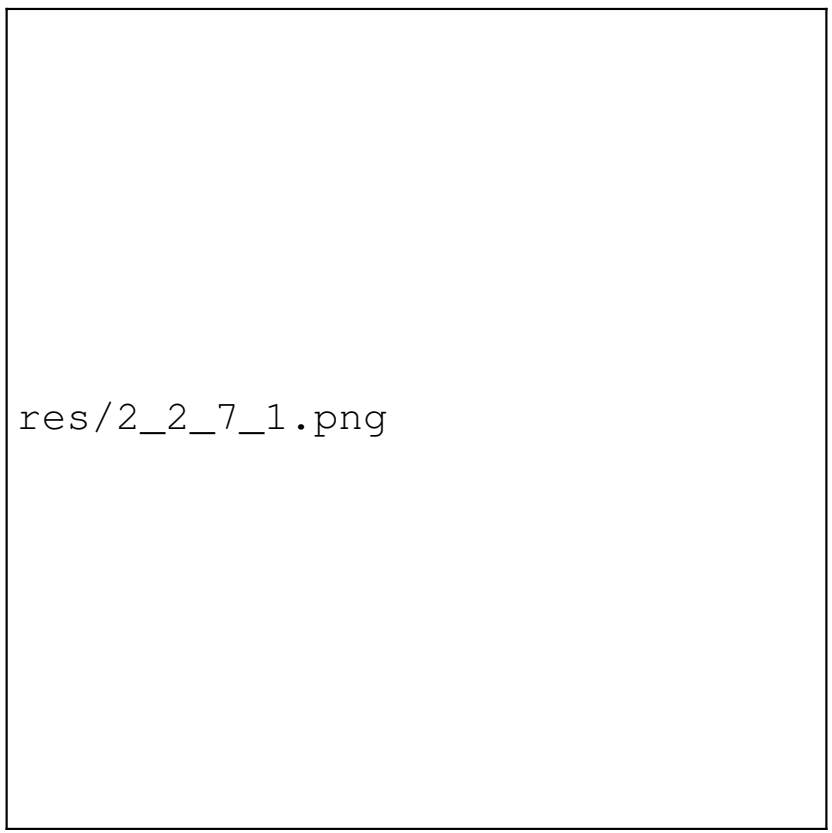
  - Random variable

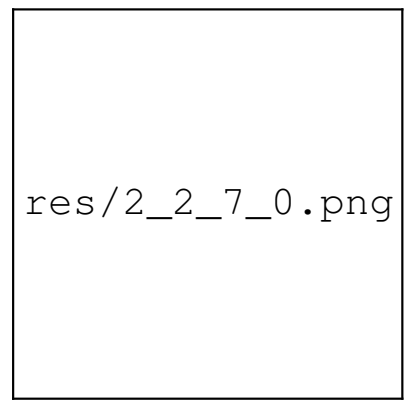
Social

A Framework for Computing the Privacy Scores of Users in Online Social Networks [**liu_framework_2010**]

		Sensitivity	β_1	...	β_n
Privacy	Attitude	User/item	item 1	...	item n
P_1	θ_1	User 1	...	...	...
...	...	...	...	R(i,j)	...
P_N	θ_N	User N	...	...	...

Table 1: An example table.





Social

Predicting friendship levels in online social networks [**ahmad_predicting_2010**]

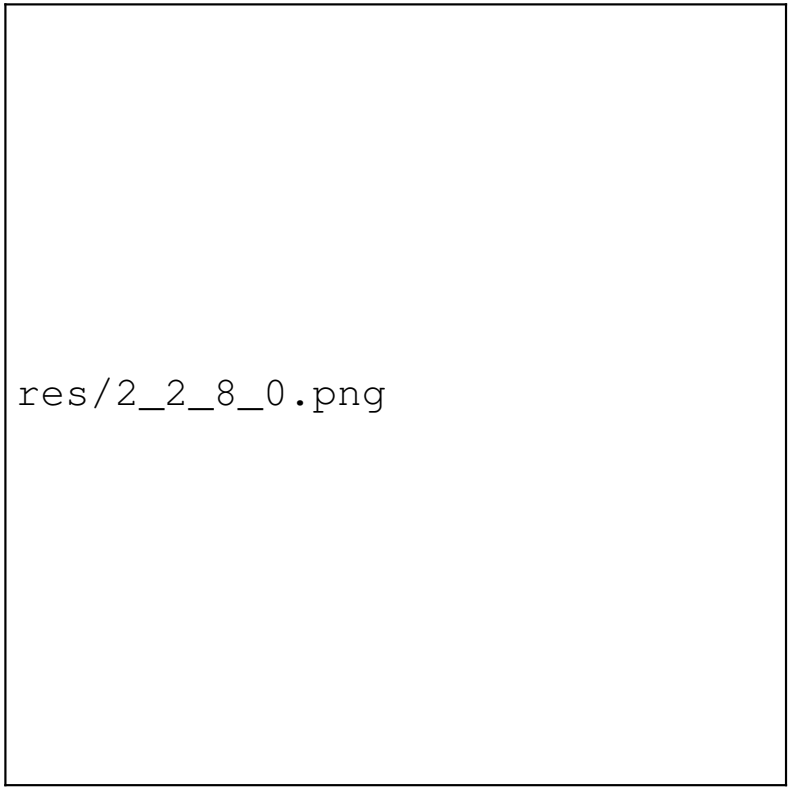
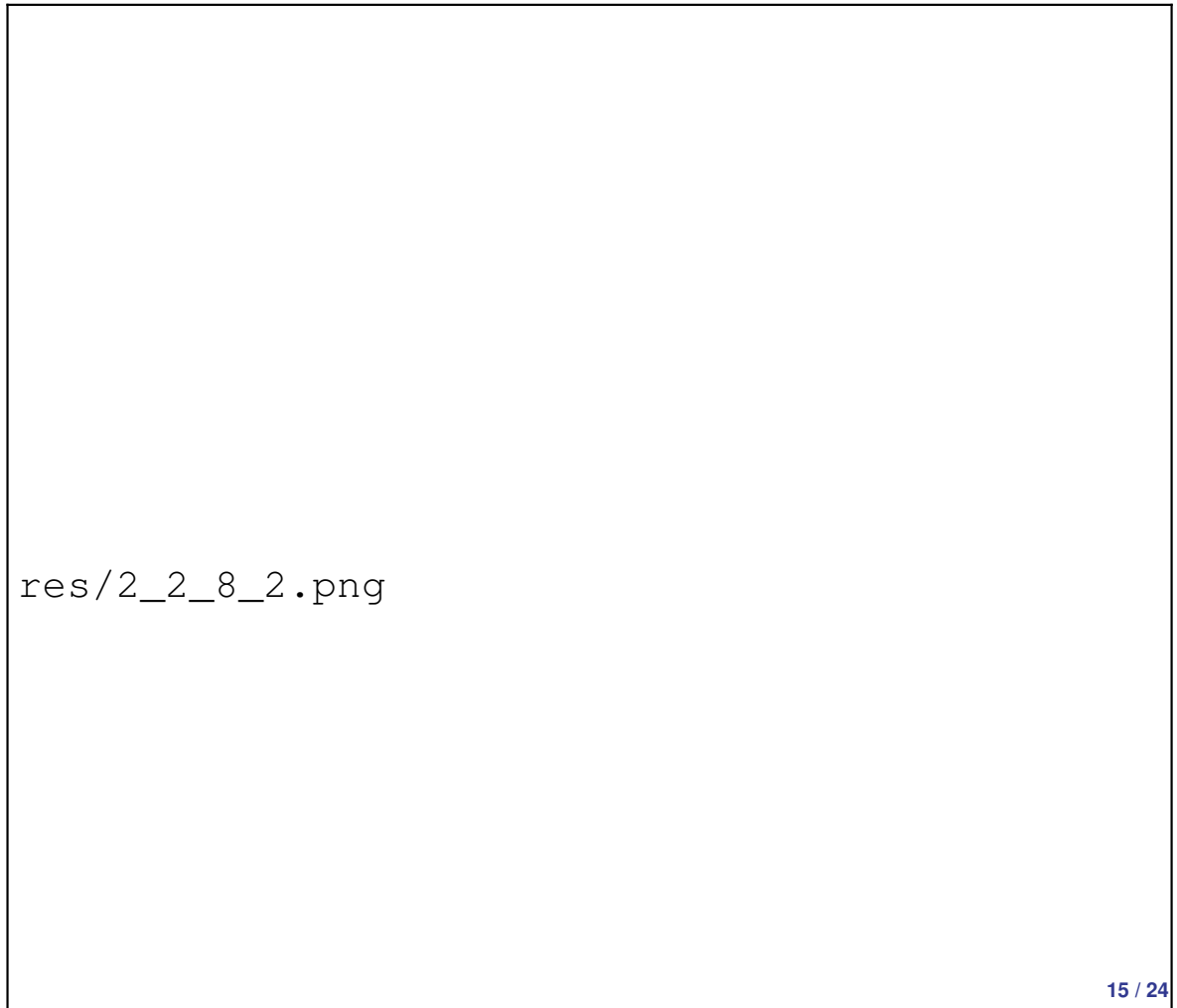


Figure 23: Levels of OSN



Social

Risks of Friendships on Social Networks [13]

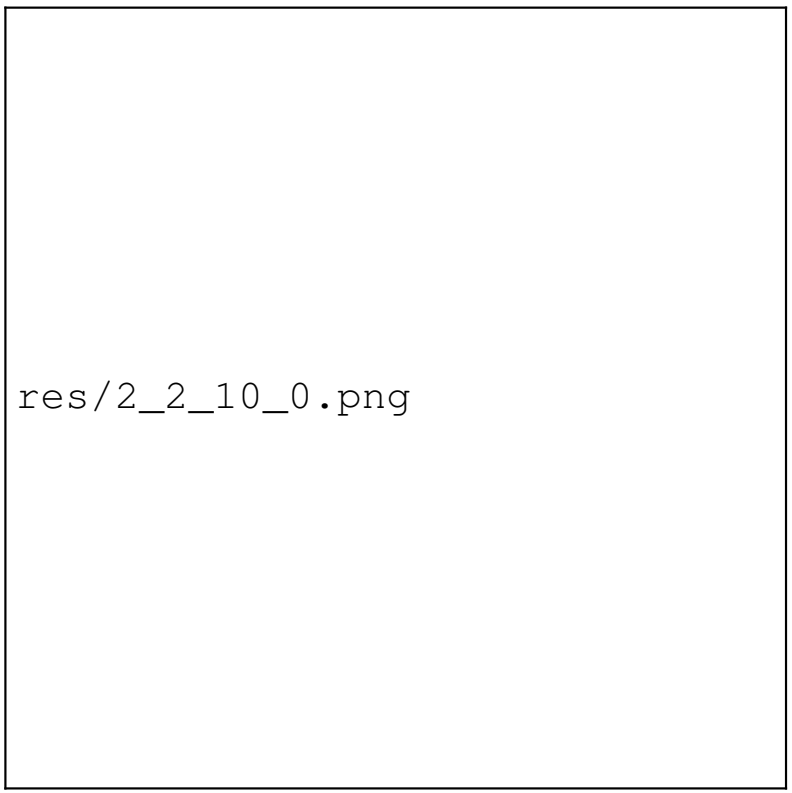


Figure 26: H

- Social Frequency Matrix for friends: N x F x n
  - N: user, F: friends, n: friends features
- Transformation:
  - Transform friends features into numerical form
  - Hometown = Rome: Hometown = 15/100
- Baseline Estimation:
  - Logistic regression analysis of features.
  - Ex: %0.9 very risky, %0.09 risky and %0.01 not risky.
- Learning Friend Impacts:
  - Past Labeling Parameter
    - PS: Profile similarity
  - Friend Impact Parameter
    - Single Impact for the Friend Cluster
    - Multiple Impact for the Friend Cluster

Social

unfriendly: Multi-party privacy risks in social networks [**thomas_unfriendly_2010**]

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Outline

Technical

Privacy-Aware Web Service Composition and Ranking [**costante_privacyaware_2013**]

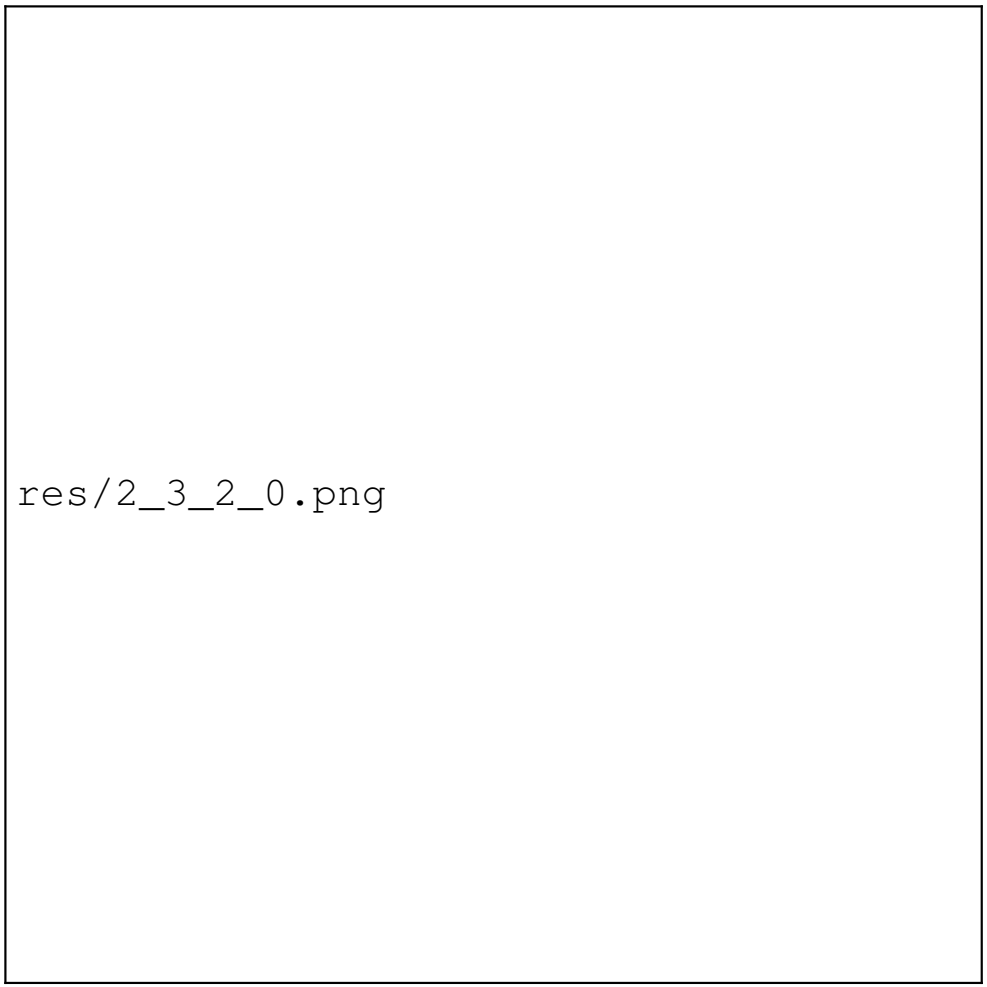


Figure 28: Privacy-Aware Architecture

Technical

Ostra: Leveraging trust to thwart unwanted communication [14]

Technical

On the Design of Socially-Aware Distributed Systems [15]

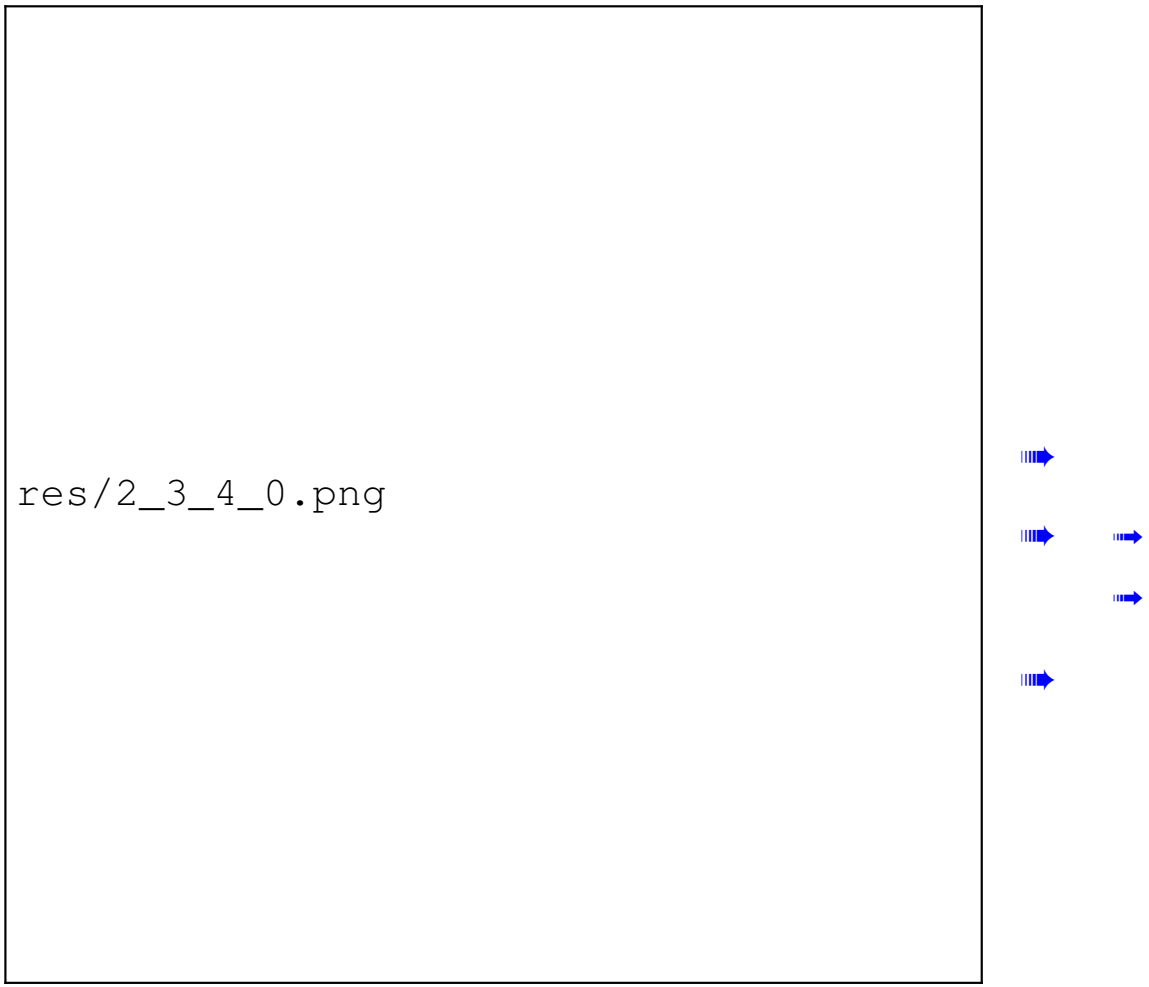


Figure 30: different system levels

Technical

A privacy self-assessment framework for online social networks [16]

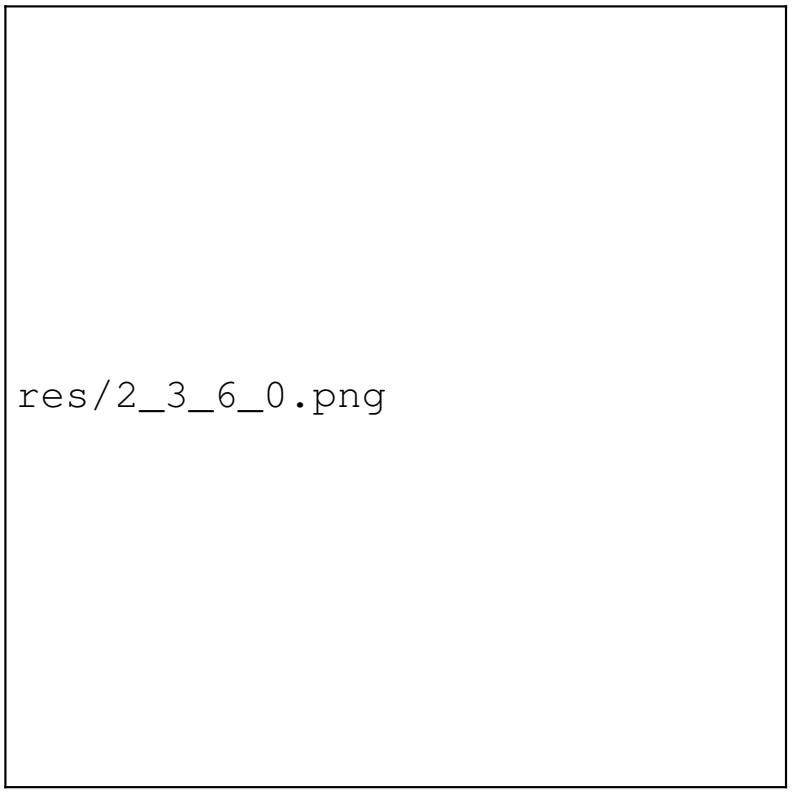
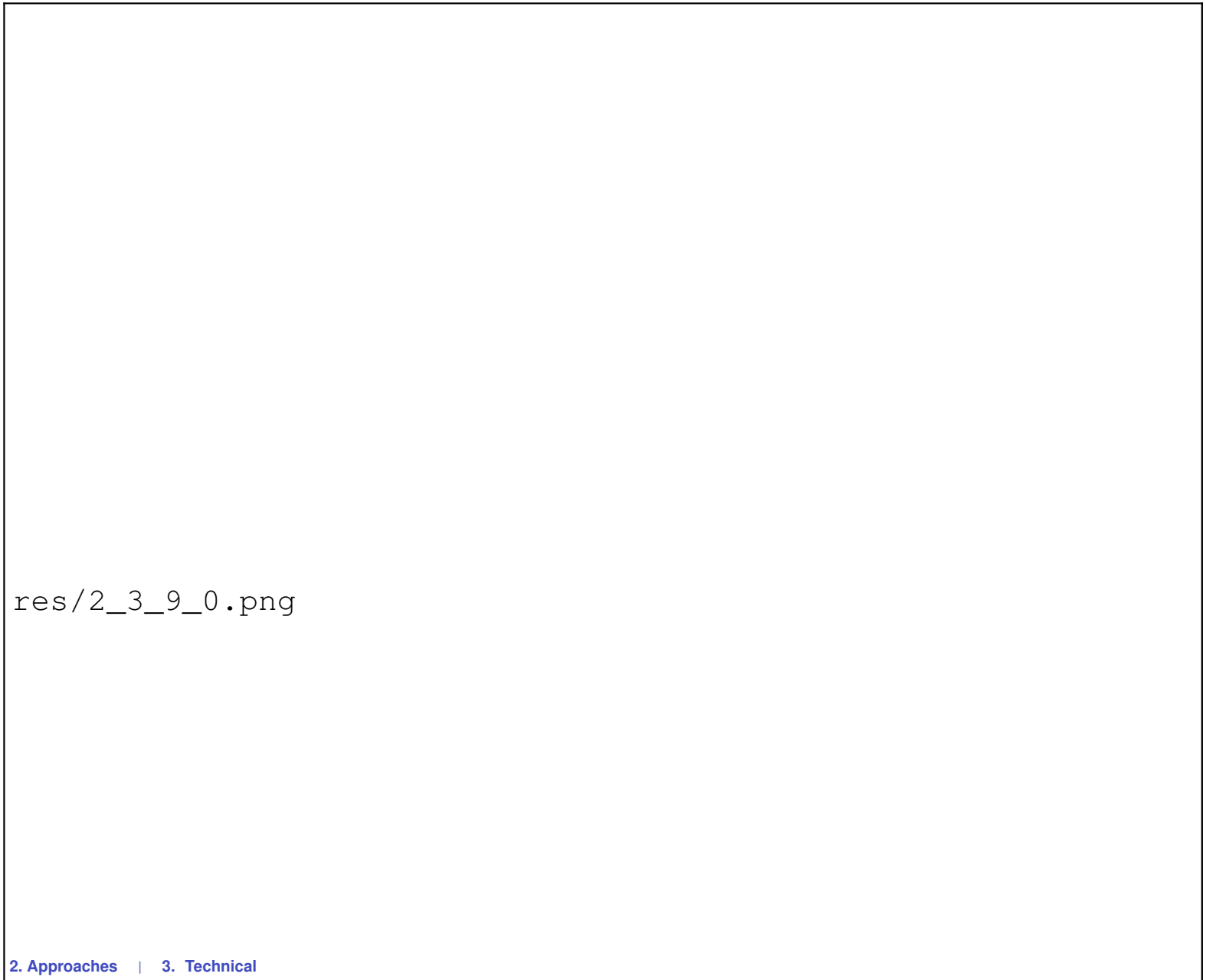


Figure 31: Privacy scores

Technical

A privacy awareness system for facebook users [17]



Technical

Identifying hidden social circles for advanced privacy configuration [**squicciarini_identifying_2014**]

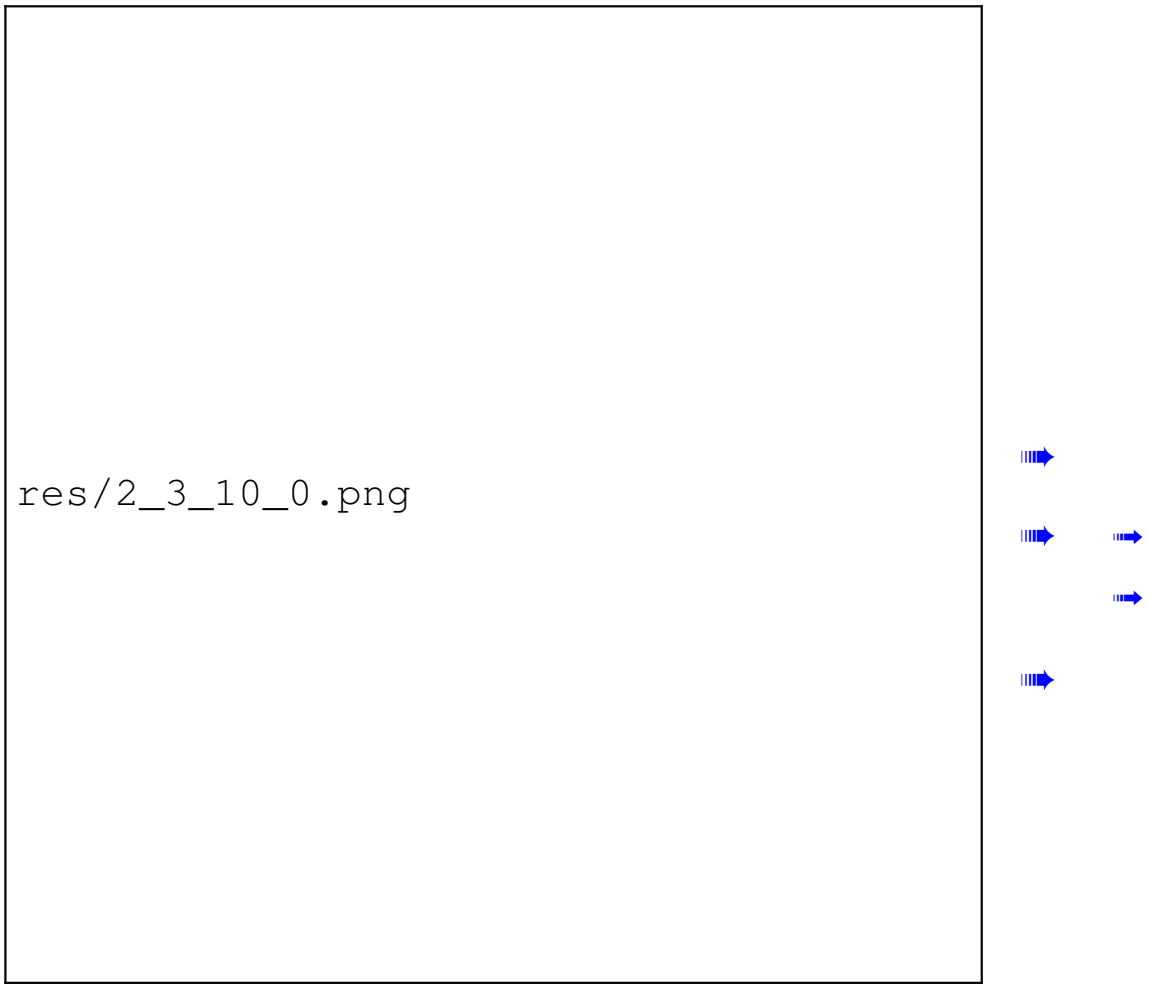


Figure 35: hghg

Outline

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[14] Alan Mislove et al. “ Ostra: Leveraging Trust to Thwart Unwanted Communication ”. In: (2008). 00193, p. 16 (p. 27).

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