Privacy score

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

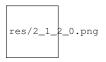


Figure 1: User privacy score-1

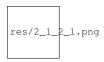


Figure 2: User privacy score-2

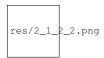


Figure 3: User privacy score-3

- 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.

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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:

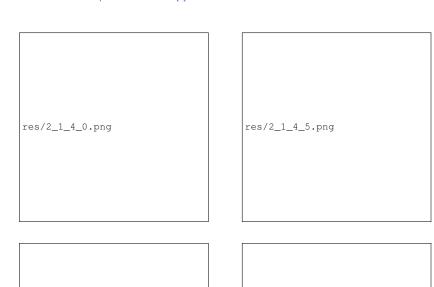
Measuring Sharing Loss:

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

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Trust Model

Computational Trust Model for Repeated Trust Games [3]



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

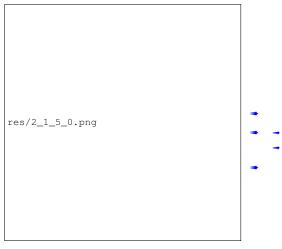


Figure 4: Cag.

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

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

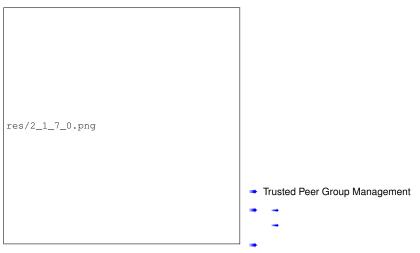


Figure 7: Geo-social Graph Representation

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

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

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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
 - * Evaluate privacy setting of a friend ...
 - * 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

V-Index: The friend that has the largest V-Index is blocked.

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

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

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- 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)

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



Figure 14: Experiment results with varying I0 and h0

Input

- → I0 [0, 1]: Disposition to privacy:
 - * Attitude of an user towards privacy of his information.
 - * I0 = 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.

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

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Figure 16: Experiment results with varying I0 and h0

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Privometer: Privacy protection in social networks [10]

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Figure 18: Information Visibility in User Profile

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Privacy impact assessment for online social networks [11]

- 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.

Figure 21: Data loss and Privacy Impact

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Privacy-triggered communications in pervasive social networks [12]

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

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- Random variable

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.

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Predicting friendship levels in online social networks [ahmad_predicting_2010]

res/2_2_8_0.png Figure 23: Levels of OSN

OSN res/2_2_8_2.png

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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

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

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Privacy-Aware Web Service Composition and Ranking [costante_privacyaware_2013]



Figure 28: Privacy-Aware Architecture

Ostra: Leveraging trust to thwart unwanted communication [14]

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

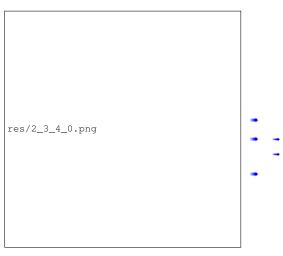


Figure 30: different system levels

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

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A privacy awareness system for facebook users [17]

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Identifying hidden social circles for advanced privacy configuration [squicciarini_identifying_2014]

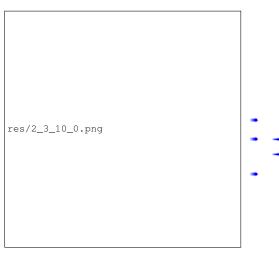
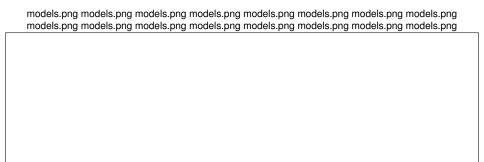


Figure 35: hghg

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3 Trust Madela

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References

pp. 370-375 (p. 19).

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[13] [14]

[16]

- [1] Aylin Caliskan Islam, Jonathan Walsh, and Rachel Greenstadt. * Privacy Detective: Detecting Private Information and Collective Privacy Behavior in a Large Social Network *. In: Proceedings of the 13th Workshop on Privacy in the Electronic Society, WPES '14. 00019. New York, NY, USA: ACM, 2014, pp. 35-46 (p. 6).
 - Hongxin Hu, Gail-Joon Ahn, and Jan Jorgensen. * Detecting and Resolving Privacy Conflicts for Collaborative Data Sharing in Online Social Networks *. In: Proceedings of the 27th Annual Computer Security Applications Conference. 00095. ACM, 2011, pp. 103–112 (p. 7).
 - Quang-Vinh Dang and Claudia-Lavinia Ignat. " Computational Trust Model for Repeated Trust Games ". In: Trustcom/BigDataSE/I SPA, 2016 IEEE. 00002. IEEE, 2016, pp. 34-41 (p. 8).
 - Aigul Kaskina. Exploring Nuances of User Privacy Preferences on a Platform for Political Participation. 00001. Université de Fribourg, 2017 (p. 10).
- [5] Nicolas Kourtellis et al. * Prometheus: User-Controlled P2P Social Data Management for Socially-Aware Applications *. In: Proceedings of the ACM/FIP/USENIX 11th International Conference on Middleware. Middleware 10.00070. Berlin, Heidelberg: Springer-Verlag, 2010, pp. 212–231 (p. 11).
 - Akansha Pandey et al. * Computing Privacy Risk and Trustworthiness of Users in SNSs *. In: 00002. IEEE, Sept. 2015, pp. 145-150 (p. 12).
 - Yongbo Zeng et al. * A Study of Online Social Network Privacy Via the TAPE Framework ... In: IEEE Journal of Selected Topics in Signal Processing 9.7 (Oct. 2015), 00003, pp. 1270-1284 (p. 14).
 - Yan Li, Zhiyi Lu, and Victor OK Li. * Algorithm to Trade off between Utility and Privacy Cost of Online Social Search *. In: Communications (ICC), 2016 IEEE International Conference On. 00000. IEEE, 2016, pp. 1–6 (p. 15).
 - B. S. Vidyalakshmi, Raymond K. Wong, and Chi-Hung Chi. * Privacy Scoring of Social Network Users as a Service *. In: Services Computing (SCC), 2015 IEEE International Conference On. 00004. IEEE, 2015, pp. 218–225 (p. 16, 17).
 - Nildhpal Talukder et al. * Privometer: Privacy Protection in Social Networks *. In: Data Engineering Workshops (ICDEW), 2010 IEEE 26th International Conference On. 00067. IEEE, 2010, pp. 266–269 (p. 18).
 - Yong Wang and Rai Kumar Negali.* Privacy Impact Assessment for Online Social Networks ". In: Collaboration Technologies and Systems (CTS), 2015 International Conference On. 00002, IEEE, 2015.
 - Murtuza Jadinvala et al. * Privacy-Triggered Communications in Pervasive Social Networks *. In: World of Wireless, Mobile and Multimedia Networks (WoWMoM), 2011 IEEE International Symposium on a. 00005. IEEE, 2011, pp. 1–6 (p. 20).
 - Cuneyt Gurcan Akcora, Barbara Carminati, and Elena Ferrari, " Risks of Friendships on Social Networks ", In: 00020, IEEE, Dec. 2012, pp. 810-815 (p. 23).
 - Alan Mislove et al. " Ostra: Leveraging Trust to Thwart Unwanted Communication ". In: (2008). 00193, p. 16 (p. 27).
 - Nicolas Kourtellis. " On the Design of Socially-Aware Distributed Systems ". In: (2012). 00011, p. 193 (p. 28).
 - Ruggero G. Pensa and Gianpiero Di Blasi. " A Privacy Self-Assessment Framework for Online Social Networks ". In: Expert Systems with Applications 86 (Nov. 2017), 00002, pp. 18–31 (p. 29).
- [17] Charles Hélou, A. Guandouz, and Esma Aïmeur. " A Privacy Awareness System for Facebook Users ". In: Journal of Information Security Research 31 (2012). 00006, pp. 15–29 (p. 30).

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