Mobile App Privacy and Security Recommendation Systems

Dillon V Stenberg

Division of Science and Mathematics
University of Minnesota, Morris
Morris, Minnesota, USA 56267

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- Over 1.5 million Apps (2015) and Over 50 billion downloads (2013)
- Each App on Android devices have data permissions
- Both Google Play and Apple have their own recommendation method
- Two recommendation methods
  - SPAR
  - Privacy-Respect App

Figure: Android Smartphone

Source: gadget-report.eu

What are some potential risks?

- Downloading an App allows access to your device and information
- Apps can access information based on their data permissions
- Apps can send and store your private information
- Survey Says! (International Data Group)
  - 54% wouldn't download an App
  - 30% removed an App

Outline

1. Background
2. SPAR
3. Privacy-Respect App Recommendation Model
4. Conclusion

1. Background
   - Data Permissions
   - Latent Matrix Factorization
2. SPAR
3. Privacy-Respect App Recommendation Model
4. Conclusion

Data Permissions

Android OS has a data permission framework

- What is a data permission?
- `READ_CONTACTS`, `ACCESS_FINE_LOCATION`

What makes a data permission dangerous?

- Depends on the user
- Depends on how the permission is used
- Some consider these to be dangerous
    - `READ_SMS`
    - `READ_CALL_LOG`

Matrix Factorization

- What is a latent matrix factorization model?
- Latent Variables: a variable that is not directly observed (directly measured), but are inferred from other variables that are observed

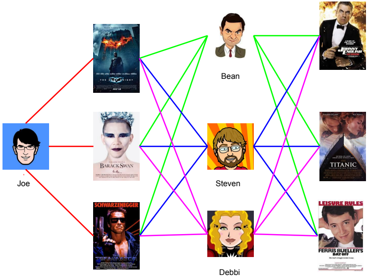


Figure: Example of recommending movies to users

Security and Privacy aware mobile App Recommendation (SPAR)

- Estimates risk scores for each App
- Ranks each App by risk score and popularity
  - Modern Portfolio Theory approach used to balance popularity and user privacy preferences
- Create an *App Hash Tree* to efficiently recommend Apps

Evaluating Risk Scores

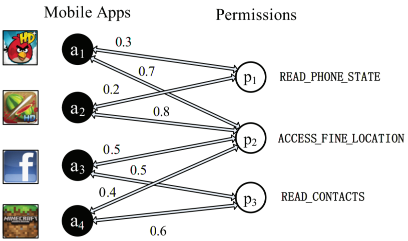
- Risk score is used to reflect the security level
- The lower the score, the safer it is to use the App

Challenges

- Difficult to assign risk scores based on permissions because some are ambiguous and are understood poorly
- Considering latent relationship between Apps and permissions
- Develop a scalable approach to refine the risk scores: Bipartite Graph

Bipartite Graph

- The bipartite graph is used to build the connections between Apps and their permissions
- Learns the security risk of each App by learning the probability of an App requesting a permission



Assigning Risk Score to Apps

- A probabilistic approach called Naive Bayes with information Priors (PNB) is used for assigning the risk scores to each App
- A technique to construct classifiers: models that assign class labels to problem instances

Naive Bayes with information Priors

- *Bayes theorem*: describes the probability of an event based on conditions related to that event
- The Beta Distribution is used as an information prior to describe probability

Coefficient of Variance (CV)

- Algorithm constructed to appropriately divide the Apps in their security levels
- Risk scores of each App compared to parameter δ
  - If the risk score is greater than δ, then that App is placed in a new security level
  - If not, then the App is put into the appropriate security level

App Hash Tree

- *Hash Tree*: a tree that has labeled nodes of values that have child nodes in different hierarchies
- Two hierarchies: Security and Category
- Hash tree is used for efficiently recommending Apps to users

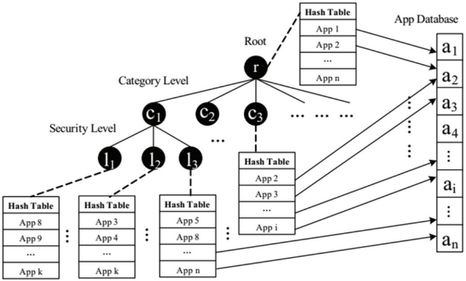
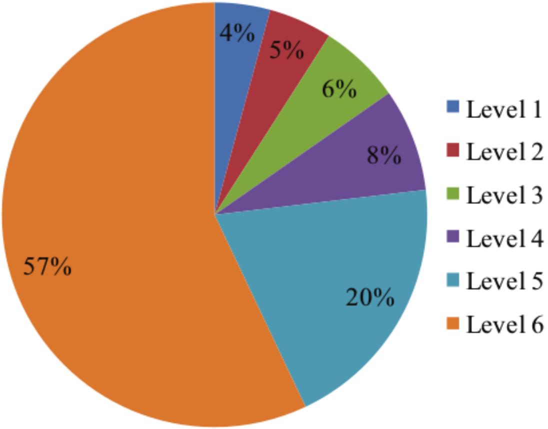


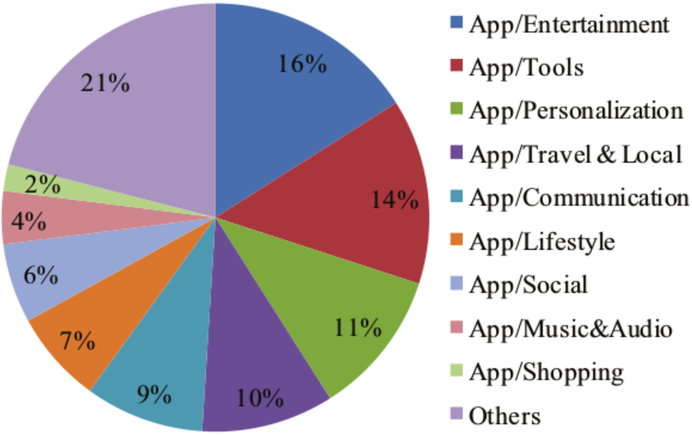
Figure: Example of the App hash tree

Data Collected

- 170,753 Apps in 30 different categories, with 173 unique security permissions
    - Took top 100 and bottom 100 ranked Apps from SPAR
- Zhu et el. manually labeled 200 secure Apps and 200 insecure Apps
- Merged Apps into a pool which includes 496 unique Apps
- Had each App judged by at least 3 users
    - Gave each App a score of 2 (insecure), 1 (not sure), or 0 (secure)
    - Gave label based on the App profile, their own experience, and other users



(a) All Levels


16%
14%
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7%
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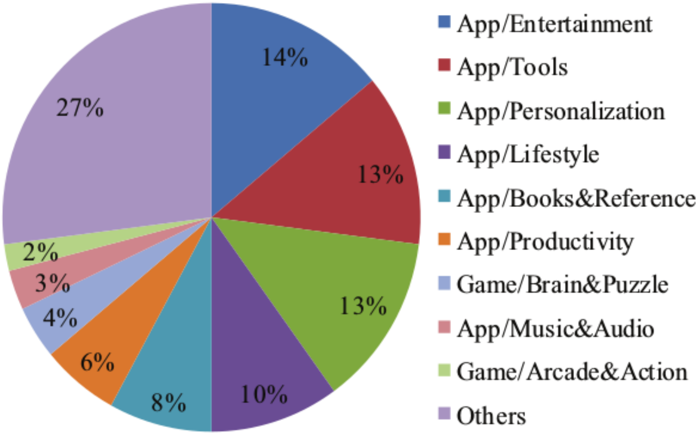
4%
2%
21%
App/Entertainment
App/Tools
App/Personalization
App/Travel & Local
App/Communication
App/Lifestyle
App/Social
App/Music&Audio
App/Shopping
Others

(b) Level 1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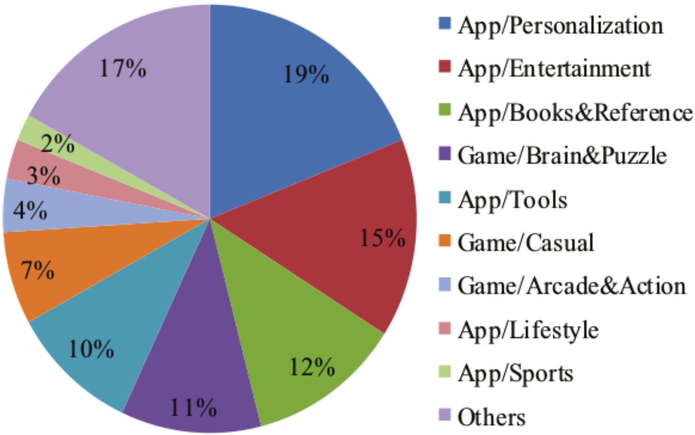
App/Entertainment
App/Tools
App/Personalization
App/Lifestyle
App/Books&Reference
App/Productivity
Game/Brain&Puzzle
App/Music&Audio
Game/Arcade&Action
Others

(c) Level 3


19%
15%
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7%
4%
3%
2%
17%
App/Personalization
App/Entertainment
App/Books&Reference
Game/Brain&Puzzle
App/Tools
Game/Casual
Game/Arcade&Action
App/Lifestyle
App/Sports
Others

(d) Level 6

Three Methods Tested

- SPAR
- PNB
- RankSVM: a learning-to-rank approach that analyzes data and recognizes patterns by the relationship of a specific query

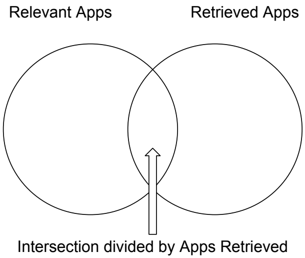
Four Evaluation Metrics

- Normalized Discounted Cumulative Gain (NDCG)
- $\text{Precision@K} = \frac{|\{\text{Relevant Apps} \cap \text{Retrieved Apps}\}|}{|\{\text{Retrieved Apps}\}|}$
- $\text{Recall@K} = \frac{|\{\text{Relevant Apps} \cap \text{Retrieved Apps}\}|}{|\{\text{Relevant Apps}\}|}$
- $F@K$ is the balance of precision and recall.

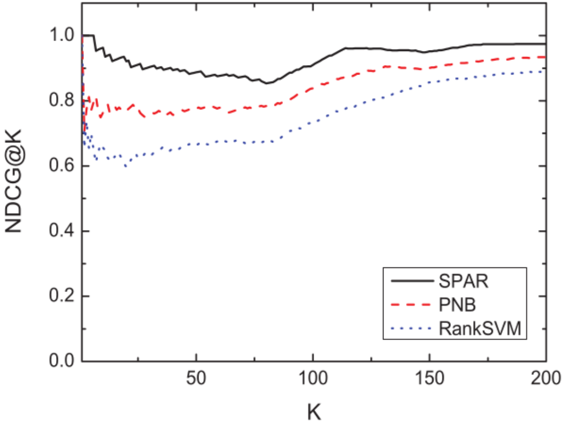
NDCG

- $\mathrm{NDCG}_p = \frac{\mathrm{DCG}_p}{\mathrm{IDCG}_p}$
- $\mathrm{DCG}_p = rel_1 + \sum_{i=2}^{p} \frac{rel_i}{\log_2(i)}$
- Highly relevant Apps appearing lower in a search result list should be penalized as the graded relevance value is reduced logarithmically proportional to the position of the result
- Being normalized means ordering the relevance ranks of the users most relevant to not relevant
- IDCG is the max sum of normalized DCG ordering

Venn Diagram of Precision@K

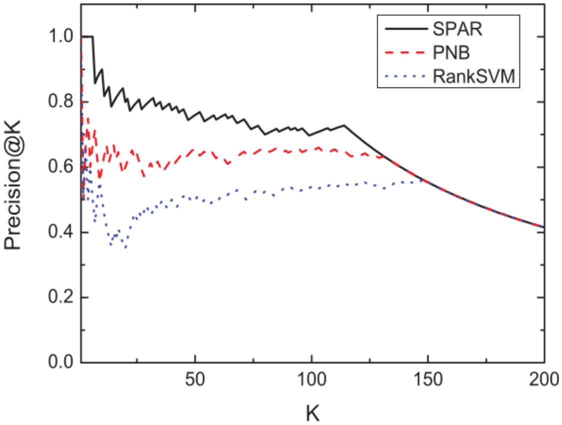


Overall Performance



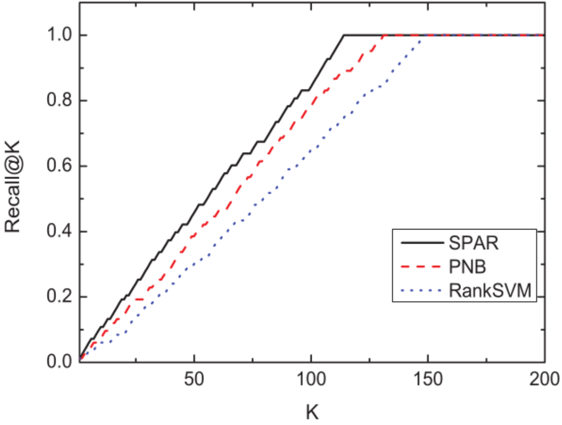
(a) $NDCG@K$

Overall Performance



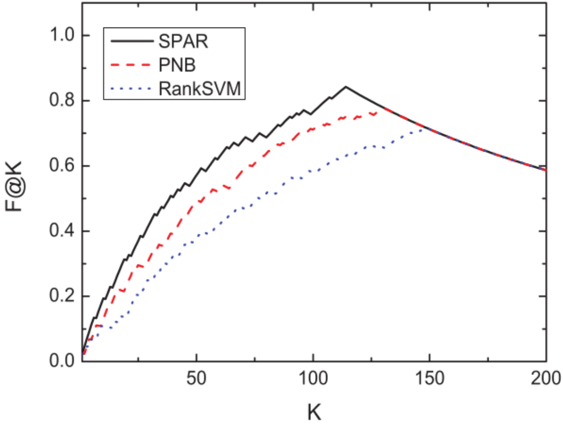
(b) $Precision@K$

Overall Performance



(c) $Recall@K$

Overall Performance



(d) $F@K$

Overview

- Construct a new latent factorization model to capture the trade-off between App functionality and user privacy preference
- Define a hierarchy of three levels of privacy used to characterize users' privacy preferences
- A crawler is created to crawl through a real world dataset

Privacy Levels

- Level I: 10 resources
- Level II: 10 resources from Level I and 23 security permissions
- Level III: Resources and permissions from Level II as well as resources Internet and Bluetooth. 72 total security permissions

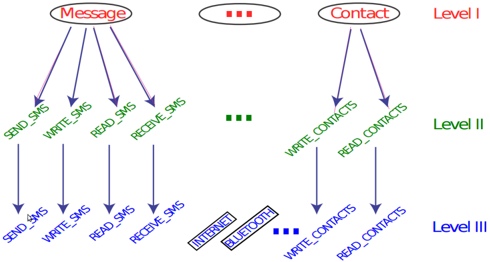


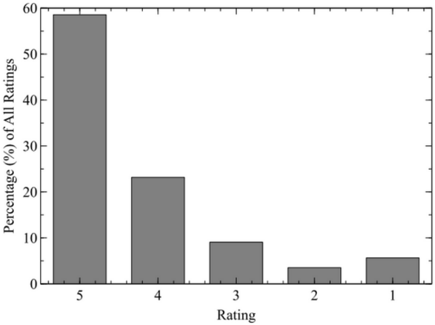
Figure: Illustration of the three levels of privacy

Constructing a Latent Factorization Model

- Modeling functionality match: Model based on standard latent factorization from other models (SVD)
- Modeling privacy respect: Modeled based on the privacy levels, describes user privacy preference and App's privacy information
- Trade-off between privacy and functionality: User's overall preference

User Profile Latent Factor

- Combine the privacy preference and user interest vectors into one vector
  - Combining them can reduce parameters to learn and will improve computational efficiency
- Poisson Distribution used to help model User Profile by user ratings data
  - It can better rank the preference order



Crawling Through the Dataset

- Obtained Google ID of a user
- Crawler is created to retrieve all the Apps that a user rated
- 16,344 users, 6,157 Apps, and 263,054 rating observations

Three Privacy Variants

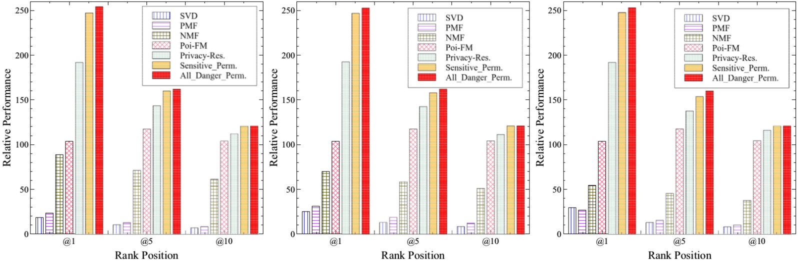
- `Privacy_Res`: Privacy-respect App recommendation with Level I privacy level.
- `Sensitive_Perm`: Privacy-respect App recommendation with Level II privacy level.
- `All_Danger_Perm`: Privacy-respect App recommendation with Level III privacy level.

Relative Performance

- A user is presented with a list of recommendations of top-N ranked Apps that have the highest predicted values
- Evaluate each approach on the Apps that were adopted by the user
- rPrecision@N $= \frac{\text{Precision@}N}{|C_{\text{adopted}}|/|C|}$
- rRecall@N $=$ rPrecision@N: Called Relative Performance
- C denotes the candidate Apps

Overall Performance

K is the latent dimension or cut-off of recommended Apps



(a) $K = 20$ (b) $K = 30$ (c) $K = 50$

Figure: Relatvie performance @N with different latent dimensions K

Conclusions

- Results show that both recommendation methods perform better over previous methods
    - SPAR was shown to be more effective and efficient
    - Privacy-Respect App privacy variants were shown to outperform other methods
- Implying that considering user privacy preference on personalized App recommendations is important

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Thank you for your time

Contact Info

- stenb061@morris.umn.edu

Questions?