Attacks on collaborative recommender systems

Agenda

- Introduction
- Charactarization of Attacks
- Attack models
- Effectivness analysis
- Countermeasures
- Privacy aspects
- Discussion

Introduction / Background

- **(Monetary) value of being in recommendation lists**
  - Individuals may be interested to push some items by manipulating the recommender system
  - Individuals might be interested to decrease the rank of other items
  - Some simply might may want to sabotage the system ..
- **Manipulation of the "Internet opinion"**
  - Malevolent users try to influence behavior of recommender systems
    - System should include a certain item very often/seldom in its recommendation list
- **A simple strategy?**
  - (Automatically) create numerous fake accounts / profiles
  - Issue high or low ratings to the "target item"

  ⇨ **Will not work for neighbor-based recommenders**

  ⇨ **More elaborate attack models required**

  ⇨ **Goal is to insert profiles that will appear in neighborhood of many**

Example profile injection

- **Assume that a memory-based collaborative filtering is used with:**
  - Pearson correlation as similarity measure
  - Neighborhood size of 1
    - Only opinion of most similar user will be used to make prediction

	Item1	Item2	Item3	Item4	…	Target	Pearson
Alice	5	3	4	1	…	**?**	
User1	3	1	2	5	…	5	-0.54
User2	4	3	3	3	…	2	0.68
User3	3	3	1	5	…	4	-0.72
User4	1	5	5	2	…	1	-0.02

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Attack	**5**	**3**	**4**	**3**	**…**	**5**	**0.87**

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Attack

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User2	4	3	3	3	…	2	[illegible]
User3	3	3	1	5	…	4	-0.72
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Attack	**5**	**3**	**4**	**3**	**…**	**5**	**0.87**

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Attack

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Characterization of profile insertion attacks

- **Attack dimensions**
  - Push attack:
    - Increase the prediction value of a target item
  - Nuke attack:
    - Decrease the prediction value of a target item
  - Make the recommender system unusable as a whole
- **No technical difference between push and nuke attacks**
- **Nevertheless Push and Nuke attacks are not always equally effective**
- **Another differentiation factor between attacks:**
  - Where is the focus of an attack? Only on particular users and items?
  - Targeting a subset of items or users might be less suspicious
  - More focused attacks may be more effective (attack profile more precisely defined)

Characterization of profile insertion attacks

- **Classification criteria for recommender system attacks include:**
  - **Cost**
    - How costly is it to make an attack?
    - How many profiles have to be inserted?
    - Is knowledge about the ratings matrix required?
      - usually it is not public, but estimates can be made
  - **Algorithm dependability**
    - Is the attack designed for a particular recommendation algorithm?
  - **Detectability**
    - How easy is it to detect the attack

The Random Attack

- **General scheme of an attack profile**

Item1	…	ItemK	…	ItemL	…	ItemN	Target
r_1	…	r_k	…	r_l	…	r_n	X
selected items			**filler items**		unrated items		

  – Attack models mainly differ in the way the profile sections are filled

- **Random attack model**
  – Take random values for filler items
    - Typical distribution of ratings is known, e.g., for the movie domain (Average 3.6, standard deviation around 1.1)
  – Idea:
    - generate profiles with "typical" ratings so they are considered as neighbors to many other real profiles
  – High/low ratings for target items
  – Limited effect compared with more advanced models

The Average Attack

- **use the individual item's rating average for the filler items**
- **intuitively, there should be more neighbors**
- **additional cost involved: find out the average rating of an item**
- **more effective than Random Attack in user-based CF**
  - But additional knowledge is required
- **Quite easy to determine average rating values per item**
  - Values explicitly provided when item is displayed

Effectiveness

- **By the way: what does effective mean?**
- **Possible metrics to measure the introduced bias**
- **Robustness**
  - deviation in general accuracy of algorithm
- **Stability**
  - change in prediction for a target item (before/after attack)
- **In addition: rank metrics**
  - How often does an item appear in Top-N lists (before/after)

Bandwagon Attack

- **Exploits additional information about the community ratings**
- **Simple idea:**
  - Add profiles that contain high ratings for "blockbusters" (in the selected items); use random values for the filler items
  - Will intuitively lead to more neighbors because
    - popular items will have many ratings and
    - rating values are similar to many other user-profiles
- **Example: Injecting a profile with high rating values for the *Harry Potter* series**
- **Low-cost attack**
  - Set of top-selling items/blockbusters can be easily determined
- **Does not require additional knowledge about mean item ratings**

Segment Attack

- **Designing an attack that aims to push item A**
- **Find items that are similar to target item,**
  - These items probably liked by the same group of people
  - Identify subset of user community that is interested in items similar to A
- **Inject profiles that have**
  - high ratings for fantasy novels and
  - random or low ratings for other genres
- **Thus, item will be pushed within the relevant community**
- **For example: Push the new Harry Potter book**
  - Attacker will inject profile with positive ratings for other popular fantasy books
  - Harry Potter book will be recommended to typical fantasy book reader
- **Additional knowledge (e.g. genre of a book) is required**

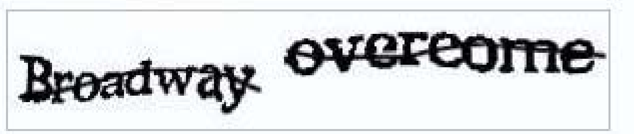
Special nuke attacks

- **Love/hate attack**
  - Target item is given the minimum value
  - Filler items are given the highest possible rating value
  - Serious effect on system's recommendations when goal is to nuke an item
  - Other way around (push an item) it is not effective
- **Reverse bandwagon**
  - Associate target item with other items that are disliked by many people.
  - Selected item set is filled with minimum ratings

Effectiveness analysis

- **Effect depends mainly on the attack size (number of fake profiles inserted)**
- **User-based recommenders:**
  - Bandwagon / Average Attack:
    - Bias shift of 1.5 points on a 5-point scale at 3% attack size
  - Average Attack slightly better but requires more knowledge
  - 1.5 points shift is significant; 3% attack size means inserting e.g., 30,000 profiles into one-million rating database …
- **Item-based recommenders**
  - Far more stable; only 0.15 points prediction shift achieved
  - Exception: Segment attack successful (was designed for item-based method)
  - Hybrid recommenders and other model-based algorithms cannot be easily biased (with the described/known attack models)

Countermeasures

- **Use model-based or hybrid algorithms**
  - More robust against profile injection attacks
  - Accuracy comparable with accuracy of memory-based approaches
  - Less vulnerable
- **Increase profile injection costs**
  - Captchas
    - 

  - Low-cost manual insertion …

Countermeasures II

- **Use statistical attack detection methods**
  - detect groups of users who collaborate to push/nuke items
  - monitor development of ratings for an item
    - changes in average rating
    - changes in rating entropy
    - time-dependent metrics (bulk ratings)
  - use machine-learning methods to discriminate real from fake profiles

Privacy aspects

- **Problem:**
  - Store and manage sensitive customer information
- **Detailed customer profiles are the basis for market intelligence**
  - Such as segmentation of consumers
- **Ensuring customer privacy**
  - important for success of a recommender system
  - users refrain from using the application if privacy leaks get publicly known

Privacy aspects II

- **Main architectural assumption of CF-Recommender system is**
  - One central server holding the database and
  - the plain (non-encrypted) ratings are stored in this database
- **Once an attacker achieved access to that system, all information can be directly used**
- **Prevent such privacy breaches by**
  - Distributing the information or
  - Avoiding the exchange, transfer or central storage of the raw user ratings.

Data perturbation

- **Main Idea: obfuscate ratings by applying random data perturbation**
- **Server although does not know the exact values of the customer ratings**
  - Accurate recommendation can still be made because:
    - The range of data is known
  - Computation based on aggregation of obfuscated data sets
- **Tradeoff between degree of obfuscation an accuracy of recommendation**
  - The more "noise" in the data,
    - the better users' privacy is preserved
    - the harder the approximation of real data for the server

Data perturbation II

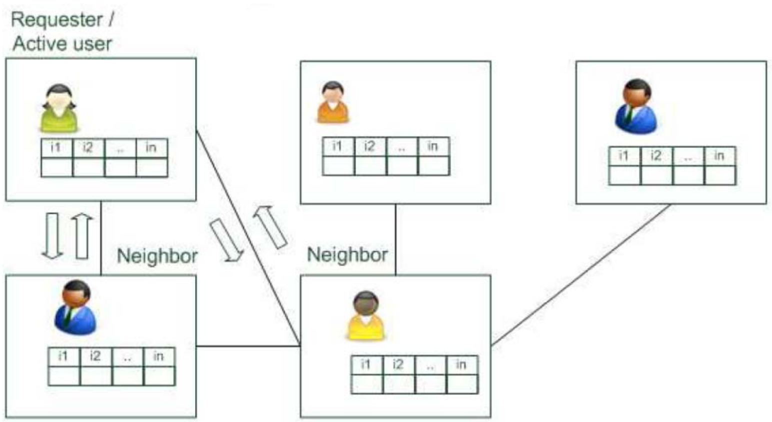
- Vector of numbers $A = (a_1, \ldots, a_n)$ provided by client
- Disguise A by adding vector $R = (r_1, \ldots, r_n)$
- $r_1, \ldots, r_n$ taken from uniform distribution $[-\alpha, \alpha]$
- Pertubed vector $A' = (a_1 + r_1, \ldots, a_n + r_n)$ sent to server
- Server does not know original ratings but
  - If range of distribution is known and
  - enough data are available

good estimation can be made of the sum of the vectors:

$$\sum_{i=1}^{n}(a_i + r_i) = \sum_{i=1}^{n}(a_i) + \sum_{i=1}^{n}(r_i) \approx \sum_{i=1}^{n}(a_1)$$

Distributed collaborative filtering

- **Distribute knowledge and avoid storing the information in one central place**
- **Peer-to-peer (P2P) CF**
  - Exchange rating information in a scalable P2P network
  - Active user broadcasts a query (vector of user´s item ratings)
  - Peers calculate similarity between recieved and other known vectors
    - If similarity > threshold, known ratings returned to requester
    - If not, query forwarded to the neighboring peers
  - Activ user calculates prediction with recieved ratings



Distributed collaborative filtering with obfuscation

- **Combines P2P data exchange and data obfuscation**
- **Instead of broadcasting the "raw" profile only obfuscated version is published**
- **Peers received this broadcast return a prediction for target item**
- **Active user**
  - collects these answers and
  - calculates a prediction using standard nearest-neighbor-method
- **Obfuscation will help to preserve privacy of participants**
- **Advisable to perturb only profiles of respondent agents**
- **Obfuscation of requester profile deteriorates recommendation accuracy**

Distributed CF with estimated concordance measures

- **Picks up tradeoff problem "privacy vs. accuracy"**
- **Main idea: Do not use standard similarity measure (like Pearson)**
- **Instead: concordance measure with comparable accuracy to Pearson etc.**
  - Given set of items rated by user A and user B. Determine:
  - number of concordant
    - Items on which both users have the same opinion
  - number of discordant
    - Items on which their disagree
  - number of items for which their ratings are tied
    - Same opinion or not rated item
  - Association between A and B computed by Somers' d measure

$$d_{A,B} = \frac{NbConcordant - NbDiscordant}{NbItemRatingsUsed - NbTied}$$

Community-building and aggregates

- **Participants of knowledge communities share information**
  - inside the community or
  - with outsiders
- **Active user can derive predictions from shared information**
- **Informations are aggregated based on e.g. SVD**
- **Individual user ratings are not visible to users outside the community**
- **Use of cryptographic schemes for secure communication between participants in the network**

Discussion & summary

- **Research on attacks**
  - Vulnerability of some existing methods shown
  - Specially-designed attack models may also exist for up-to-now rather stable methods
  - Incorporation of more knowledge-sources /hybridization may help
- **Practical aspects**
  - No public information on large-scale real-world attack available
  - Attack sizes are still relatively high
  - More research and industry-collaboration required