Detecting Real Money Traders in MMORPG by Using Trading Network

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Help the online game operators

- Focusing on Massively Multiplayer Online RPG
  - Thousands of players co-exist in one virtual “world”
    - cf. millions of registered players
Operators’ issue: Grasp the virtual world

- To facilitate further growth
  - Effect of features
    - Extended game fields, one-shot events
  - Influential players
    - Mentoring, intermediation, trades

- To maintain the order of the virtual world
  - Harassments between players
    - Player killing, occupation of specific locations
  - Causes that lead unfairness and crisis of virtual economy
    - Real Money Trading, use of bots, cheat
RMT: Real Money Trading

- Real money ↔ Virtual properties
  - Currency, items, status, functions, avatars, etc.
  - Observed in other online services, e.g., SNS, auction

- Two opposing attitudes (sometimes ambivalent)
  - **Positive**: Means of augmenting the real world
    - e.g., Second Life
  - **Negative**: Source of serious problems
    - e.g., Most MMORPGs in Japan
Task & given situation

- Automatic detection of RMTers
  - Actual log data is available
    - Now with TECMO KOEI GAMES CO., LTD.
    - Prefer title independent features
  - Operators want no arms race
    - Desire un-cheatable features
  - Operators’ verification is indispensable
    - To avoid ruling out honest players
    - The amount of human resource depends on situation
      - Title (scale, seriousness) and budget for operation
      - Prefer unsupervised or semi-supervised methods
Outline

1. Introduction
2. Approach
3. Procedure
4. Experiment
5. Conclusion
As a binary classification

- Classify each character into RMTer or non-RMTer
  - Supervised machine learning [Ahmad+, 09]
    - Naïve Bayes, k-NN, AdaBoost, etc.
    - Various features (incl. those specific to the title)
  - Not flexible: Too much/less positive class
As a ranking problem

- Sort characters according to their suspiciousness
  - Using cumulative features [Itsuki+, 10]
    - Handled currency
      - dealing with enormous virtual currency
    - Volume of actions
    - Activity hours
  - Not thoroughly studied

Ranking:

1st  2nd  3rd  4th  5th  6th  7th
Connection between pairs of characters

- Extremely low exchange rate, e.g., full of wallet =
  - Division of RMT labor & frequent trade
- Infrastructure for trading → log data are available

Volume of individual trade
Trading sub-network (from our data)

- RMTers and their trading partners in one timeframe
  - Division of labor of RMTers
    - Typical roles
      - Seller
      - Earner
      - Collector
  - Tight connection
Communities in the trading network

Possibility of wholesale arrest
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Overview

Raw log data

Step 1. Extracting communities from trading network

Step 2. Ranking characters
Step 1. Community extraction

- Graph partitioning / graph clustering
  - Node: Character
  - Edge: Trade between two characters
Which division is best?
Quality of a given division of network

- Modularity [Newman+, 04]

\[ Q = \sum_i (e_{ii} - a_i^2) \]

- Many edges in each community → Large \( Q \)
- Expected value of link ratio: to avoid a trivial solution

\[ \frac{\sum_{e \in E_i} (\text{weight of } e)}{\sum_{e \in E} (\text{weight of } e)} \]

\[ \frac{\sum_{e \in A_i} (\text{weight of } e)}{\sum_{e \in E} (\text{weight of } e)} \]

- \( E \): Set of all edges in the network
- \( E_i \): Set of edges within \( i^{th} \) community
- \( A_i \): Set of edges connecting to a node in \( i^{th} \) community
Community extraction algorithm

- Finding a partitioning that maximizes $Q$: NP-hard
- A bottom-up greedy algorithm [Clauset+, 04]
  1. Regard each node as a community and calculate $\Delta Q$ for each connected community pair
  2. Merge two communities whose $\Delta Q$ is largest (and $>0$)
  3. Update $\Delta Q$ for the merged communities
  4. Repeat steps 2 & 3 while $Q$ gains
Step 2. Ranking characters

- Frequent and/or large-scale trades $\rightarrow$ RMT
  1. Ranking communities
     - In-community trades
  2. Ranking characters in each community
     - Trades of individual character
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Application to a real MMORPG

“Uncharted Waters Online”
- Exploration, naval battle and trading in mid-ages
- RMT is prevalent

4 timeframes (15〜23 days, no overlap)
- RMTers are identified (& banned) manually
  - 29〜130 (<1%) within 15,249〜18,745 characters
- Actual action log data in the same period
  - 300〜480 million records

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Traders and RMTers

- Obs.
  - Half of all characters traded something
  - 1/3 of all characters traded virtual currency
  - Most of RMTers traded virtual currency
    - Only 1 exception in period D
### Target characters and weight of trade
- **All traders**
  - tb: binary
  - tt: # of times
- **Currency traders**
  - cb: binary
  - ct: # of times
  - cv: volume

### Obs.
- Weights of trades / focusing on currency → fine-grained
- RMTers → only a few communities (1-8)
Evaluation metrics for RMTer detection

- Available human resource is unknown
  - It varies depending on the situation

- Two measures
  - Balance between Recall and Precision
    - Recall (R): how exhaustively RMTers are identified
    - Precision (P): how correctly system identifies RMTers
  - Avg. Precision at various recall

1 RMTer is found
2 RMTers are found
3 RMTers are found
... All RMTers are found
Parameter selection of proposed method (1/2)

- Representation of trading network
  - All traders
    - tb: binary
    - tt: # of times
  - Currency traders
    - cb: binary
    - ct: # of times
    - cv: volume

- Measure for in-community trades
  - tt: # of trade transactions
  - ct: # of currency transactions
  - cv: Total volume of traded currency

- Measure for trades of individual character
  - tt: # of trade transactions
  - ct: # of currency transactions
  - cv: Total volume of traded currency
Parameter selection of proposed method (2/2)

- 45 combinations → 10
  - Representation of trading network (5)
    - Different network achieved the best result in different period
  - Measure for in-community trades (3 → 1)
    - Volume of traded currency \((cv)\) > # of transactions \((tt, ct)\)
  - Measure for trades of individual character (3 → 2)
    - Traded currency \((ct, cv)\) > All trade \((tt)\)

- Implications
  - Large amount of currency is exchanged for RMT
    - RMTers dealt with more than 1/3 of total currency trades
  - Virtual currency is popular in RMT
    - Buyers want virtual currency
Baselines: direct assessment of each char.

- Sort characters based on handled currency (cv)
- Two supervised methods (w/o constants)
  - Naïve Bayes
    - with multinomial distribution [McCallum+, 98]
    \[
    \text{Score}(c) = \sum_{a \in A(c)} \text{freq}(a, c) \log \frac{P(a|\text{RMTer})}{P(a|\text{non-RMTer})}
    \]
  - Support Vector Machines [Vapnik, 99]
    - with linear kernel (SVM\text{light} is used)
    \[
    \text{Score}(c) = \sum_{x_i \in X} y_i \alpha_i K(x_i, c)
    \]
    \{+1: RMTer, -1: non-RMTer\}
  - Feature: all of 338 types of actions
    - trade, attack to other player, find an item, invest for a ship
Several versions beat all the baselines
- But nothing significantly wins in all periods

<table>
<thead>
<tr>
<th>Model</th>
<th>Target char. set</th>
<th>Period A $N = 29$</th>
<th>Period B $N = 52$</th>
<th>Period C $N = 106$</th>
<th>Period D $N = 130$</th>
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<tbody>
<tr>
<td>cv</td>
<td>Currency traders</td>
<td>0.320</td>
<td>0.440</td>
<td>0.484</td>
<td>*0.466</td>
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<td>MNB</td>
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<td>SVMs</td>
<td>All chars</td>
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<td>tb.cv.ct</td>
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<td>Proposed</td>
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<td>0.547</td>
<td>0.564</td>
<td>0.498</td>
<td>*0.529</td>
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</tbody>
</table>
Significant improvement

- Both on R-P curves and Avg. Prec.
- Most RMTers $\rightarrow$ a single, small, and top-rank community
  - Period A: 29 RMTers $\rightarrow$ 28 + 1
  - Period B: 52 RMTers $\rightarrow$ 50 + 1 + 1
- Some are still difficult to detect
Relatively unsuccessful cases

- Weak for plural RMTer communities
  - Period C: 106 RMTers → 53 + 33 + 19 + 1
  - Period D: 130 RMTers → 80 + 32 + 14 + 2 + 1 + 1

- Need a more intelligent ranking
  - e.g., Combination of ranks (community, character)
  - e.g., Re-ranking based on operators’ judge
Detection of RMTers in MMORPG

- As a ranking problem
- Wholesale arrest thru capturing communities
  - Low exchange rate → division of labor & frequent trade
- Evaluation using actual log data
  - Better performance than separately assessing each char.
  - w/ a room of further improvement
Future work

Technical aspect
- Further investigation into trading network
  - Mixture models [Newman+, 07]
  - Augmentation with other components [Ahmad+, 11]
- Apply state-of-the-art machine learning techniques

Evaluation
- Is arms race really overcome?
  - e.g., Robustness against disposal use of characters
- Application to other MMORPGs