Measuring #GamerGate: 
A Tale of Hate, Sexism, and Bullying

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Social Networking Services

twitter
facebook
askfm
YouTube
Yahoo Answers
Aggressive & Bullying behavior

- **Cyberbullying.** Repeated and hostile behavior by a group or an individual, using electronic forms of contact.

- **Cyber-aggression.** Intentional harm delivered by the use of electronic means to a person or a group of people who perceive such acts as offensive, derogatory, harmful, or unwanted.
Gamergate controversy

- A coordinated campaign of harassment in the online world.
- It started with a blog post by an ex-boyfriend of independent game developer Zoe Quinn, alleging sexual improprieties.
- It quickly evolved into a polarizing issue, involving sexism, feminism, and “social justice,” taking place on social media like Twitter.

Gamergate controversy provides us a unique point of view into online harassment campaigns.
Our goals

- Proposal of a principled methodology to collect content related to aggressive and bullying activities.
- Gamergate specific:
  - Quantification of this controversy.
  - Exploration of the existing differences between Gamergaters and random Twitter users.
Outline

1. Abusive dataset building
   - Data collection
   - Data processing

2. Measurement results
   - How Active are Gamergaters?
   - How Social are Gamergaters?
   - Are Gamergaters Suspended More Often?

3. Conclusions
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Overall process

Steps.

– 1. Select seed keyword(s).
– 2. Create dynamic list of keywords.
– 4. Collect a random sample*.

* Complements the abusive-related dataset with cases that are less likely to contain abusive content.
Select seed keyword(s) which are likely to relate with abusive incidents.

- E.g., #GamerGate, #BlackLivesMatter, #PizzaGate.
- Set of hate- or curse-related words, e.g., Hatebase database.

At the time, $t_i$, the lists of words to be used for filtering posted texts includes only the seed word(s): $L(t_1) = \langle seed(s) \rangle$. 
Dynamic list of keywords (I)

- Filter keywords list to select abusive-related content.
- Update dynamically - in consecutive time intervals - the filtering list.
- Depending on the topic under examination: update the filtering list at different time intervals.

Keywords list, $L(T)$

In $T = \{t_1, t_2, \ldots, t_n\}$ the $L(T)$ equals to:

$L(t_i) = <\ seed(s), kw_1, kw_2, kw_N >$, where $kw_j$ is the $j$th top keyword in time period $\Delta T = t_i - t_{i-1}$. 
Dynamic list of keywords (II)

Update dynamic list for $t_i \rightarrow t_{i+1}$

- Step 1. Investigate the texts posted at $t_{i-1} \rightarrow t_i$.
- Step 2. Extract the top $N$ keywords based on their frequency of appearance.
- Step 3. Update $L(t_i)$ with the up-to-date top $N$ keywords along with the seed word(s).

Use of the updated list at the time period: $t_i \rightarrow t_{i+1}$.
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Preprocessing

- **Cleaning.** Removal of stop words, URLs, punctuation marks, normalization (repetitive characters elimination).
- **Spam removal.** Based on the number of hashtags, and duplications.

- Study of hashtags and duplication distributions to find optimal cutoffs.
- Avg. # hashtags: 0 to 17.
- Hashtags: we set the limit to 5.
- Similarity of tweets: Levenshtein distance.
- About 5% of the users have a high percentage of similar posts.

**Final dataset:** 659k GG-related tweets, 1M random tweets.
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3 Conclusions
GGers tend to have older accounts – They are not bots.

GGers are significantly more active than random Twitter users (more posts and hashtags).
GGers have more favorites and topical lists declared than random users.

GGers post more URLs in an attempt to disseminate information about their “cause”.

GGers make more mentions within their posts — higher number of direct attacks compared to random users.
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GGers tend to have more friends and followers than random users.
The controversy appears to be a clear “us vs. them” situation.
Existence of in-group membership $\rightarrow$ heightens the likelihood of relationship formation.
Emoticons, uppercases, sentiment, emotion

Emoticons and “shouting” by using all capital letters: two common ways to express emotion.

- GGers and random users use emoticons at about the same rate.
- GGers tend to use all uppercase less often than random users.

Sentiment, Offense, & Emotion

- GGers post tweets with a generally more negative sentiment — > large proportion of offensive posts.
- GGers use more hate words than random users (Hatebase database).
- GGers and random users do not differ substantially in a variety of emotions: anger, disgust, fear, sadness, surprise.
- GGers are less joyful — > they are not necessarily angry, but they are apparently not happy.
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Twitter Reaction to Aggression

<table>
<thead>
<tr>
<th></th>
<th>active</th>
<th>deleted</th>
<th>suspended</th>
</tr>
</thead>
<tbody>
<tr>
<td>Random users</td>
<td>67%</td>
<td>13%</td>
<td>20%</td>
</tr>
<tr>
<td>Gamergate</td>
<td>86%</td>
<td>5%</td>
<td>9%</td>
</tr>
</tbody>
</table>

- Focus on a sample of 33k users from both the GG and random datasets.
- Users tend to be suspended more often than deleting their accounts by choice.
- Random users are more prone to be suspended or delete their accounts than GGers.
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GGers use Twitter as a mechanism for broadcasting their ideals (hashtags, mentions).

GGers appear to be Twitter savvy users and quite engaged with the platform (posts, participating lists, favorites).

GGers are more well-connected within their network (followers, friends).

GGers express with more negative sentiment overall, but they only differ significantly from random users with respect to joy.

GGers are less likely to be suspended due to the inherent difficulties in detecting and combating online harassment activities.
Future work

- Conduction of a more in-depth study of Gamergate controversy, focusing on how it evolved over time.

- Consideration of additional features, e.g., network-based, to further examine the differences among the GGers and random users.

- Automatically detect abusive users (upcoming HyperText paper: stay tuned!)
Questions?

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