Gendered Conversation in a Social Game-Streaming Platform

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Abstract

Online social media and games are increasingly replacing offline social activities. Social media is now an indispensable mode of communication; online gaming is not only a genuine social activity but also a popular spectator sport. With support for anonymity and larger audiences, online interaction shrinks social and geographical barriers. Despite such benefits, social disparities such as gender inequality persist in online social media. In particular, online gaming communities have been criticized for persistent gender disparities and objectification. As gaming evolves into a social platform, persistence of gender disparity is a pressing question. Yet, there are few large-scale, systematic studies of gender inequality and objectification in social gaming platforms. Here we analyze more than one billion chat messages from Twitch, a social game-streaming platform, to study how the gender of streamers is associated with the nature of conversation. Using a combination of computational text analysis methods, we show that gendered conversation and objectification is prevalent in chats. Female streamers receive significantly more objectifying comments while male streamers receive more game-related comments. This difference is more pronounced for popular streamers. There also exists a large number of users who post only on female or male streams. Employing a neural vector-space embedding (paragraph vector) method, we analyze gendered chat messages and create prediction models that (i) identify the gender of streamers based on messages posted in the channel and (ii) identify the gender a viewer prefers to watch based on their chat messages. Our findings suggest that disparities in social game-streaming platforms is a nuanced phenomenon that involves the gender of streamers as well as those who produce gendered and game-related conversation.

Keywords: Text Analysis, Gender, Social Gaming, Online Chat
1 Introduction

Simone de Beauvoir said, “One is not born a woman, but becomes one” [1], highlighting the situation of women as not free to make decisions about their life, but rather shackled by a society that objectifies them, severely limiting their actions and opportunities. Since Beauvoir’s clarion call, researchers have examined the extent to which women continue to be objectified in popular media such as television, movies, and advertisements [2]. Such media continue to reinforce women as objects under the “gaze” of men [3].

The Internet and the Web enable complex forms of many-to-many social interaction and make one’s identity less conspicuous. On first glance, they provide an ostensibly “gender-neutral” medium, offering new opportunities to empower women. However, studies suggest that inequality remains in online spaces. For instance, in the popular microblogging platform Twitter, the “glass-ceiling” effect [4] and gender-biased user dialogue [5, 6] are observed. Studies on image search engines [7] and Wikipedia [8, 9, 10] also demonstrate persistent gender stereotypes and disparities.

While data-driven research on online gender inequality has focused on several popular online platforms, online gaming has received little attention, although the advent of the Internet and of social media has transformed video games into genuine social activities [11]. Video games are no longer the purview of arcades and family rooms; they are social activities connecting people across the world, and a widely broadcasted and watched medium. Numerous online communities are devoted to discussing, watching, and playing video games. Traditionally considered a “boy’s activity” [12, 13], the culture of gaming communities has been accused of misogyny [14]. Video games themselves can be a medium that glorifies the objectification of women [15, 16, 17]. The online space of video games provides no respite from these inequities; ethnographic studies have observed that, when female gamers have revealed their identities online, gamers cease speaking about game-related topics and instead shift to the gamer herself and her gender [13, 18].

Yet, little work has systematically examined, on a large scale, the possibly gendered nature of the next evolution of social media and online video gaming: social video game-streaming platforms. On the most popular of these platforms, Twitch, gamers can stream their gameplay and communicate with viewers in real-time. To give an idea of its popularity, in 2015, Twitch had a monthly average of 1.7 million broadcasters and half a million concurrent viewers [19]. The 2013 world championship of “League of Legends”, a popular online game, was broadcast live on Twitch; the event was watched by more people than the NBA finals [20].

An interesting aspect of Twitch is that the success of e-sports has allowed some video game professionals and personalities to garner a cult following rivaling those of many celebrities. Central to the success of these individuals are their channels. In Twitch, each game stream is called a “channel” and is run by an individual streamer, a group of streamers, an organization, or a channel aggregator. Browsing the list of public channels, one can not only find a wide
Users interact via chat. A webcam shows the streamer’s reactions as he plays. Gameplay streamed live for the viewers.

Figure 1: Twitch Channel Stream Interface

variety of games — League of Legends, Counter Strike, and Hearthstone, but creative performance arts such as painting, music, and animation making. Many streamers play, in addition to their main game, other games in their channels.

Twitch facilitates communication between viewers and the streamers by providing a public chat room for each channel. Viewers can post chat messages to communicate with the streamers or with other viewers. Streamers can also post in the chat, but often streamers just share their webcam feed and talk directly in the stream. Importantly, the relationship between viewers and streamers is a potential source of income in Twitch; streamers earn revenue by holding game events, having subscribers, and encouraging donations. Fig. 1 shows the interface of Twitch which has a game feed, streamer’s webcam feed, and public chat room.

In sum, Twitch represents one of the most popular platforms for the rapidly rising form of social gaming. In Twitch, the spectacle of gaming is not only watching the video game and streamers but also the actions of the viewers themselves. With this fundamental transformation in gaming culture, where viewers and streamers both have the power to communicate and to be seen, our study investigate how gender inequality manifests in the Twitch platform, asking the following research questions:

- Are chat messages addressed to streamers gendered? Is there a relationship between the gender of a streamer and the nature of messages that the streamer receives? For instance, do female streamers receive more objectifying comments, while male streamers receive more game-related messages? Is it possible to classify the gender of a channel’s streamer by the comments they receive?

- Are viewers and their messages gendered? Do viewers choose channels based on gender? Is the gendered choice of channels correlated with objectifying language?
Our analysis on whether social game-streaming platforms exhibit gendered behavior is timely. These platforms have become a powerful and influential medium for new and young gamers alike, and this influence may have far-reaching consequences outside the domain of social media, for example by distorting beliefs about women in the real world [23].

1.1 Ethics Statement
This study was reviewed by the IRB of Indiana University Bloomington (“Gender objectification in online conversations”, protocol #1609276630).

2 Data and Methods

2.1 Data and Terminology
Our data comprises of all chat messages posted in public Twitch chat rooms between August 26th and November 10th in 2014 (76 days). There were 1,275,396,751 messages posted in 927,247 channels (1,375 messages per channel on average), by 6,716,014 viewers (190 messages per user on average). For each message the following information is available: timestamp, author, channel, and message text. Author and channel are identified by screen name; for the channel, this is the screen name of the streamer.

Similar to other social media, the activity and popularity of Twitch channels are highly skewed. We can quantify them by counting the number of messages produced by each user and channel (for activity), as well as the number of users chatting in a channel (for popularity). Fig. 2 shows the distributions of these variables.

Our analysis is based on the subset of 71,154,340 messages posted to the chats of a matched sample of 200 female and 200 male streamers. To estimate the gender of streamers we manually examined the webcam feeds from archived video feeds of past streams. We started by ranking all channels by the total number of chat messages and examined the streamers of the most active 1,000 channels. We discarded those streamers who do not share their webcam in their streams. From this initial procedure we found 102 female streamers. From this group, we discarded three streamers whose profile information was not written in English, leaving 99 English-speaking female streamers from the top 1,000 streamers. We then applied the same procedure to a random sample of less popular streamers, i.e. whose channels ranked between 1,000 and 16,000 in the chat activity distribution, and found the remaining 101 female streamers.

Having found a sample of female streamers, we identify a matched sample of male streamers. The reason for matching samples is that prior work on these data has shown that the nature of conversations on Twitch depends dramatically on chat activity [24]. In particular, as the rate of messages increases, messages become shorter and contain more emoticons. Because male streamers tend to be on average more popular than female ones, and since more popular
channels will inevitably have a higher rate of chat activity, statistical estimates of language difference may be biased. To control for this potential source of bias we thus match male and female streamers by stratifying on the channel activity distribution [25].

Because male streamers outnumber female ones, we sampled male streamers who matched the 200 female streamers identified before. We used the number of chat messages as the matching criteria; that is, every male streamer has a matching counterpart in the female streamers sample with respect to the channel activity, and not to the rank. As we did for the identification of female streamers, the gender of male streamers was manually identified and only those who used English in their profile were kept. For the remainder of this paper we refer to the top 100 channels in each gender as popular channels and the rest as less popular channels.

2.2 Statistically Overrepresented Words

As our first exploratory analysis, we detect unigrams and bigrams that are overrepresented in either male or female streamers. To do so, we use log-odds ratios with informative Dirichlet prior method [26]. The method estimates the log-odds
ratio of each word $w$ between two corpora $i$ and $j$ given the prior frequencies obtained from a background corpus $\alpha$. The log-odds ratio for word $w$, $\delta_{w}^{(i,j)}$, is estimated as

$$\delta_{w}^{(i-j)} = \log \left( \frac{\frac{y_{iw}^{i} + \alpha_{w}}{n_{i} + \alpha_{0} - (y_{iw}^{i} + \alpha_{w})}}{\frac{y_{iw}^{j} + \alpha_{w}}{n_{i} + \alpha_{0} - (y_{iw}^{j} + \alpha_{w})}} \right) +$$

$$- \log \left( \frac{\frac{y_{iw}^{j} + \alpha_{w}}{n_{i} + \alpha_{0} - (y_{iw}^{j} + \alpha_{w})}}{\frac{y_{iw}^{i} + \alpha_{w}}{n_{i} + \alpha_{0} - (y_{iw}^{i} + \alpha_{w})}} \right),$$

(1)

where $n_{i}$ (resp. $n_{j}$) is the size of corpus $i$ (resp. $j$), $y_{iw}^{i}$ (resp. $y_{iw}^{j}$) is the count of word $w$ in corpus $i$ (resp. $j$), $\alpha_{0}$ is size of the background corpus, and $\alpha_{w}$ is the frequency of word $w$ in the background corpus.

Furthermore, this method provides an estimate for the variance of the log-odds ratio,

$$\sigma^{2}(\delta_{w}^{(i-j)}) \approx \frac{1}{(y_{iw}^{i} + \alpha_{w})} + \frac{1}{(y_{iw}^{j} + \alpha_{w})},$$

(2)

and thus a $z$-score:

$$Z = \frac{\delta_{w}^{(i-j)}}{\sqrt{\sigma^{2}(\delta_{w}^{(i-j)})}}$$

(3)

By leveraging the informative prior obtained from the background corpus, this method often outperforms other methods such as PMI (point-wise mutual information) or TF-IDF, particularly in detecting significant differences of frequent words without over-emphasizing fluctuations of rare words [26, 27].

### 2.3 Word and Document Embeddings

To characterize individual users and channels we create a document for each channel (and user) by aggregating every chat message in the channel (by the user). Then we jointly obtain vector-space representations of words, users, and channels by using the paragraph vector (doc2vec) method [28], which is an extension of the popular word2vec embedding method [29]. This joint embedding not only allows us to do vector operations across documents and words, but has been argued to outperform other document embedding methods in document similarity comparison tasks [30]. We use the skip-gram with negative sampling (SGNS) model to learn word vectors. Among two main doc2vec models — distributed memory (DM) and distributed bag of words (DBOW) — here we use the DBOW model because of its conceptual simplicity, efficiency, and reported superior in performance [30]. We use the doc2vec implementation available in popular gensim Python library [31]. The dimension of vectors is set to 100 and the window (skip-gram) size is set to 5. The model is trained with 10 epochs. All source code and the models used in this paper are available on Github.\(^1\)

\(^{1}\)https://github.com/...
3 Results

3.1 Exploratory Language Analysis

We perform a term-based exploratory analysis to identify gendered terms. We group channels based on their popularity (i.e., popular vs. less popular) and gender, producing four “documents”: ‘popular male’, ‘popular female’, ‘less popular male’, and ‘less popular female’. To remove channel-specific terms, we keep only words that are used in at least 100 channels, 20 female channels, and 20 male channels. We make two comparisons: popular female vs. popular male and less popular female vs. less popular male. We compute log-odds ratio (see §2.2) for unigrams and bigrams by using the word frequency in the entire Twitch dataset as the prior. The terms are ranked by their estimated z-scores and the 25 terms with the largest absolute z-score values are selected and visualized. The z-scores of the displayed words range from 175 to 17. The identified words are then manually categorized into four categories — streamer ids, game-related jargon, objectifying cues, and miscellaneous — by using the information available in Twitch and other online forums. By objectifying cues, we mean language that reduce women to their body or appearance [32] or as objects to be owned or used [33].

Popular channels display a clear contrast between two genders (Fig 3, left). Game-related words are clearly overrepresented in male channels while words that signal objectification are strongly associated with female channels. Interestingly, such words are not apparent in less popular female channels. Instead, the words that signal social interactions such as “hello”, “bye”, and “song” (i.e., automated playlist requests) stand out in female channels. Also note the word “warning”. This may suggest that the less popular female channels tend to have stronger moderation in place, and tend to be used more as a social gathering than a sporting event.

We repeat the same process for bigrams, which illustrate a similar pattern (Fig. 3, right). Among popular channels, those belonging to female streamers are characterized by terms, presumably directed at the streamer, about their physical appearance; male channels are instead associated with more game-related terms. Again, less popular female channels do not show clear signs of objectification. Additionally, the results show the contrasting use of second-person and third-person pronouns across popular and less popular channels. In popular channels, even though objectifying cues seems to be directed to the streamer, other bigrams are in third-person. By contrast, less popular channels are dominated by second person pronouns. This observation suggests that direct communication with the streamer dominates in less popular channels while participating in popular channels resembles watching sporting events.

3.2 Analyzing Channels

To identify lexical features from female and male channels we train document embedding models for the selected 400 channels. To identify non-trivial gen-
Table 1: Channel classification learned features

|       | Doc2vec | BoW          |
|-------|---------|--------------|
| Female| cute, beautiful, smile, | hi, boobs, song, hello, |
|       | babe, lovely, marry,     | tess, emily, cat, love, |
|       | boobs, gorgeous, omg, hot| cassie, kittens         |
| Male  | epoch, attempts, consistent, reset, shields, fastest, | frankerz, game, chris, got, |
|       | devs, slower, melee, glitch| adam, aviator, level, chief, |
|       |                      | arv, kynan             |

After the preprocessing we train the doc2vec model (see Sec. 2.3). As noted, both document vectors and word vectors are trained jointly. We visualize the vectors by applying t-SNE, a popular manifold learning (dimensionality reduction) method [34]. The map suggests clustered structure based on gender (see Fig. 4).

We then train two classifiers that predict the gender of a streamer by using L2 regularized logistic regression with two sets of features: bag of words (BoW) and doc2vec. We evaluate the model by using 5-fold cross validation. As a baseline, we use BoW model with 10,000 features using TF-IDF vectorization [35]. This model exhibit the accuracy of 74% (± 0.11%, 95% confidence interval) and a mean AUC of 0.80 in ROC curve for the holdout test set. Then we use the normalized document vectors as the features, obtaining an accuracy of 87% (± 0.07%, 95% confidence interval) and a mean area under curve of 0.93.

Let us examine the key features. For the BoW model, we identify the words that correspond to the largest absolute coefficient values (see Table 1). For the doc2vec-based model, because it is not straightforward to connect each feature to a word, we use a different approach; Since the doc2vec model learns documents and words vectors in the same vector space, we simply identify the words that are most clearly identified as a female or male document. We first extract the top 10,000 words based on frequency in the channel corpus, then identify the words that result in the highest (lowest) probability values in our classification model (see Table 1).

Our results indicate that female channels are characterized by words about physical appearance, the body, relationships, and greetings while male channels are characterized by game-related words. Male channels are also associated with many uncommon words, suggesting that the male channel chats are more diverse while the content in female channels share common words that signal objectification. In sum, both our exploratory analysis and classification exercise suggests that the answer to our first main research question — “are the chat messages that streamers receive gendered?” — is “yes”.

Table 2: Distribution of users who posted only in female or male channels

|                                              | Female | Male  |
|----------------------------------------------|--------|-------|
| Only Popular Channels                        | 14,849 (74%) | 17,168 (78%) |
| Both                                         | 3,576 (18%)    | 2,672 (12%)    |
| Only Less Popular Channels                   | 1,829 (9%)   | 2,089 (10%) |
| Total                                        | 20,185 (100%) | 21,883 (100%) |

3.3 Analyzing Individual Users

Now we turn our attention from the streamers and the chat messages that they receive to the viewers and the messages that they produce. We ask whether the viewers and their chat messages are also gendered, by examining gender preferences in channel selection by users, and their linguistic differences.

We examine whether the selection of which channels to post to is associated with a given gender by calculating, for each user, the percentage of female channels that they posted among all (400) channels. 1,818,028 individual users posted at least one message in at least one of the 400 channels. We narrow it down to 93,898 (5%) active users who have posted at least 100 messages, primarily to obtain reliable language models. Our result suggests strong gender preference in channel selection (see Fig. 5). Note that if choices were random we would expect a binomial distribution with a peak at 50%. By contrast, we see a strong gender divide. A large fraction of users (16%), even when we focus on the users who have posted in more than five channels, have posted only in male or female channels. Moreover, if we limit ourselves to users who have posted in many (10+) channels, a clear peak at 100% — 10 female-channels and 0 male-channels — is visible, indicating that the choice of chat participation is gendered and a significant fraction (8%) of users post messages only in female-streamer channels. Among 93,898 active users, there are 20,185 users and 21,883 users who posted only in female or male channels respectively. Most of these users has posted messages in popular channels (see Table. 2).

Let us examine the linguistic differences between those strongly gendered users. As described before, a user’s chat messages is considered as a document and its vector-space representation is obtained using doc2vec model. From 42,068 users who posted only in male or female channels, we randomly selected 10,000 (24%) users (4,802 are female-only viewers) and examine them closely. We first visualize their document vectors with t-SNE (Fig. 6 left).

The map shows a clear separation between the two types of users, suggesting clear lexical differences. The map also shows distinct clusters. We study the meaning of these clusters by identifying strongly associated words for each cluster. Specifically, given a cluster of \( n \) document vectors \( C = \{ d_1, d_2, \ldots, d_n \} \), we find every word \( w \) that is close to many of the documents vectors, satisfying
the following condition:

$$\frac{|\{d \in C | S_c(d,w) \geq s_{\text{min}}\}|}{|C|} \geq f_{\text{min}},$$  \hspace{1cm} (4)$$

where $S_c(d,w)$ is the cosine similarity between two vectors $d$ and $w$, and $s_{\text{min}}$ and $f_{\text{min}}$ are two free parameters. We use $s_{\text{min}} = 0.4$ and $f_{\text{min}} = 0.9$.

We select eight clusters from the t-SNE map and identify characteristic words for them (shown in Table 3). The characteristic words clearly signal the ‘topic’ of the cluster, which we use as labels (see Table 3 and Fig. 6). For instance, every representative words in the “League of Legends (LoL)” cluster represents either a position (“junglers”) or a character (“thresh”) in the game. Some of the identified clusters are related to streamers (“Kaceytron”, “Kitty”, “Trick2g”) and some are related to games (Dota, League of Legends (LoL), Super Smash Bros (SSB), Dark Souls). We can also see two clusters related to Spanish language and chat moderators. The terms in the “Mods” cluster are the ids of the users who are known as moderators for multiple channels.

| Cluster               | Representative Words                     |
|-----------------------|-----------------------------------------|
| Dota                  | mirana, slark, qop, potm, furion, slader, lycan, bristle |
| LoL (League of Legends)| champ, junglers, thresh, liss, azir, morg, riven, nid |
| DarkSouls             | freja, lucatiel, drangleic, artorias, darklurker, estus, smelter, dragon |
| SSB (Super Smash Bros.)| ness, dedede, palutena, fow, wario, shulk, miis, jiggz |
| Kaceytron             | kaceytron, kacey, kacey, catcam, kaceytrons, objectify, poopbutt, objectifying |
| Kitty                 | kitty, kittyplaysgames, moonwalk, kittys, kittythump, kittyapprove, catday, kittysub |
| Trick2g               | trick, godyr, dyr, dcane, trklata, trkcane, trkhype |
| Mods (Moderators)     | superfancymicorn, tsagh, omeed, ironcore, tobes, snago, ara, moblord |
| Spanish               | dividir, jajajaja, palomas, carajo, belleza, negrito, aca, peruano |

Table 3: Representative words for the identified clusters using doc2vec and t-SNE.

To glean the relationships between these gendered users and their language, we first pick the two most gender-biased words from Sec. 3.1: “points” and “boobs”. We then calculate the cosine similarity between each of the word and user document vectors to identify the user document vectors that are most similar to one of the two words. The top 250 users for each word are selected and overlaid on top of the t-SNE map in Fig. 6 (Right). The two groups of users
are clearly separated on the map. Interestingly, the identified user clusters tend to contain only one set of users. For instance, “Kaceytron” cluster is full of users whose vectors are highly similar to the vector for “boobs”, suggesting that the chat messages made by these users share high semantic similarity with the word “boobs”. Indeed, not only she portrays a highly controversial stereotype of female gamer (e.g. “attracting viewers with cleavage”), but also her channel is famous for not banning anyone nor filtering any comments, and for directly responding to abusive comments [36]. By contrast, the “Trick2g” — a famous streamer for his game commentaries — cluster only contains users who share the context with “points”.

Inspired by clear separability of users based on their gendered language, we analyze how these gendered viewers are distributed with other gendered word pairs. First, we manually selected eight gendered word pairs from our exploratory analysis in Sec. 3.1. From these pairs, we calculate the difference vector between the two word vectors; given a pair of words, a game-related one $w_g$ and an objectifying one $w_o$, we calculate $\vec{v}_{g\rightarrow o} = \vec{w}_o - \vec{w}_g$. This vector, which roughly estimates the semantic difference between those two vectors, is then used to project and compare each user document vector. A positive cosine similarity value means the user vector is closer to $\vec{w}_o$ and a negative value suggests the user vector is closer to $\vec{w}_g$. The results, shown in Fig. 7, confirm our intuition. Viewers who only post in female-streamer channels tend to share similar context with words that signal objectification, while those who post in male-stream channels only tend to share similar context with game-related words.

Our analysis suggests that gendered viewers should be clearly separable based on their language. So, we build classifiers; again, we train logistic regression classifiers with BoW and doc2vec features. In an evaluation using 5-fold cross-validation, BoW features achieve an accuracy of 96% (± 0%, 95% confidence interval) and a mean area under curve of 0.99 in ROC curve, while doc2vec features achieve 88% (± 1%, 95% confidence interval) accuracy and a mean area under curve of 0.95 in ROC curve. The BoW model performed surprisingly well in this classification task. However, our feature analysis shows that it is a result of identifying trivial features. Table 4 lists the most important features in BoW model and most of them are channel-specific terms such as streamer IDs. By contrast, the key doc2vec features, inferred by the method described above, are more general gendered terms.

So far our main focus has been on the majority of users, who post only in male or female channels. Next, in order to verify whether objectifying traits are prevalent only in gender-biased individuals, we select a set of 2,734 balanced users who posted an approximately equal amount of messages in both female and male chat rooms (female chat percentage between 40-60%). We then separate those chat messages into two groups based on the gender of the streamers and build classification models to predict the gender of the streamer whose chat the message was written in. Similar to previous analysis we train two classification models: one using doc2vec, and another using BoW. The latter has an accuracy of 91% (± 0.02, 95% confidence interval) while the former 81% (± 0.01, 95%
Table 4: User classification learned features

| Doc2vec | BoW |
|---------|-----|
| **Female** | gorgeous, beautiful, makeup, wig, cute, marry, dress, perv, pervert, smile |
|          | lea, kaceytron, cat, boobs, kitty, sheever, lacey, sonja, hafu, dizzy |
| **Male**  | ridley, quad, melee, cirno, glitch, unlocked, leaderboards, mechanic, resets, rebirth |
|          | hutch, nelson, chris, boogie, warowl, fow, nickel, amp, aeik, moe |

Table 5: Classification features of balanced users

| Doc2vec | BoW |
|---------|-----|
| **Female** | beautiful, cute, marry, cat, makeup, hair, cleavage, hot, boyfriend, costume |
|          | kitty, boobs, lea, emily, tits, kaceytron, ally, alisha, hafu, becca |
| **Male**  | bungie, gp, replay, hltv, jayce, blackscreen, comeback, vs, lp, chopper |
|          | moe, nelson, hutch, abdou, coty, chris, arnie, mr, boogie, bbg |

confidence interval). Surprisingly, the learned features from both of these methods are similar to the features learned from the analysis of users who post only in a specific gendered channels (see Table 5), suggesting that objectification is not a result of individual gender preferences, but is commonplace.

4 Discussion

We reveal a nuanced picture of gendered conversation in Twitch, a social game-streaming platform. Returning to the research questions we posed, our analysis on both streamers and viewers shows that the conversation in Twitch is strongly gendered. First, the streamer’s gender is significantly associated with the types of messages that they receive — male streamers receive more game-related messages while female streamers receive more objectifying messages. Second, the streamer’s gender is also significantly related to the channels viewers choose to watch. Many viewers choose to watch and comment in only male or female channels and their messages are similarly gendered; the messages posted by users who comment only in female channels tend to have semantic similarity with objectifying cues while those who comment only in male channels tend to have semantic similarity with more game-related terms. Even the users who post in both male and female channels maintain similar linguistic distinction based on gender; when posting to female channels they tend to choose messages that have semantic similarity to objectifying cues.
Yet, we cannot unequivocally say that Twitch is a conversational hotbed for gender stereotyping. In particular, the popularity of channels seems to change the nature of chat, not only in terms of information overload [24], but also in terms of objectification, moderation, and conversational structure. Objectifying cues are only prevalent in popular female channels. Less popular channels instead exhibit comments from viewers that represent chat moderation. Moreover, the user document embedding technique reveals that there exist user clusters that consist of famous moderators, indicating that strong, effective moderation is in place for many less popular female-streamer channels. Pronoun usage also changes depending on the popularity of channels; less popular channels are characterized by usage of second-person pronouns, signaling more intimate conversation between viewers and streamers, while popular channels exhibit the pattern that viewers are talking about streamers, except when they make objectifying remarks.

We analyzed the language of users by employing multiple computational methods. Our approach of using log-odds ratio with informative Dirichlet prior and the doc2vec method effectively revealed the gendered nature of chat messages. doc2vec allowed us to look at words and documents in the same space and also performed better than the BoW features in document classification. t-SNE and vector arithmetic proved useful in identifying clusters of terms and users. Our methods contribute to growing literature on constructing language models to identify and unpack gendered phenomena; for instance, we can draw parallel to models by Fu et al. [37] that found questions posed by journalists to professional female tennis players objectified women, while questions posed to male players focused were game-related, and by Way et al. [38], who found subtle gender inequalities in faculty hiring practices among universities of different rankings and career trajectories.

We acknowledge that our analysis has several limitations. Most notably, we provide only a static picture of Twitch limited to questions about association rather than causal relationships. While we can only surmise the causes of the gendered conversation we observed, financial motivations may commodify and incentivize the objectification of female streamers. Twitch provides revenue for streamers through a subscription system, and many streamers also deploy donation systems for additional revenue. Thus, financial incentives exist for streamers to increase subscribers and possibly to conform to the requests of the male viewers, the majority of many streamers' "customers". Such incentives may solidify the popularity of female streamers who do not address (or even encourage) objectification, facilitating abusive behavior against female gamers. This vicious cycle may reinforce and spawn the structural problem of gender imbalance in online social gaming communities. If part of feminism’s remit is to consider how society, females included, may play a role in constructing what a legitimate female’s identity is in, for example, online spaces, we argue that we should investigate how Twitch supports heteronormative stereotypes. Future work may also examine how pathways to popularity differ for male and female channels. For instance, do female-streamer channels gradually evolve to conform to gender stereotypes or allow objectifying comments?
Our study also does not investigate how streamers themselves engage viewers and the chat. There are a wide range of streamers from those who play games without talking or chatting to those who actively engage with viewers through frequent gaming events for their audience. Analyzing streamer behavior is a challenging task requiring analysis of both the audio and video feeds of streamers; emerging techniques for analyzing multimedia data may facilitate future work examining the interplay between streamer behaviors and viewer behaviors.

Last but not least, our work points to the need to examine the vast number of small communities, albeit not so popular, on Twitch whose conversations do not follow gender lines. Our analysis shows the existence of vigilant user groups who provide moderation services to ensure the conversations revolve around game-related topics. This observation paints a less bleak picture of social gaming. Might there be a way to bridge between these two disparate spaces of crowded and intimate spaces? Developing methods for automatic detection of abusive and objectifying comments as well as other scalable communication and moderation techniques will also be beneficial for online gaming communities.

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Figure 3: Statistically over-represented n-grams in female and male channels

**Left:** unigrams. **Right:** bigrams. Font size is proportional to the $z$-score.

### Popular

**Female**
- kitty
- kaceytron
- queen
- goal
- ign
- omg
- raffle
- instagram
- que
- chair
- cats

**Male**
- bitch
- boobs
- tits
- show
- cosplay
- cute
- beautiful
- pussy
- fat
- hair
- marry
- love
- frankerz
- molly
- chris
- shadow
- sun
- sick
- answer
- man
- bro
- case
- dude

### Less Popular

**Female**
- league
- stream
- kappa
- bibliothump
- keppo
- song
- lol
- sleep
- girl
- head
- added
- night
- twitter
- donate
- follow
- chat
- wanna
- bye
- hello
- songrequest
- omg
- warning
- queue

**Male**
- love
- level
- raid
- run
- steam
- win
- game
- time
- man
- great
- dude
- think
- first
- think
- dude
- started
- long
- hard
- well
- good
- inst
- still
- got

### Additional Seeds

**Female**
- your_boobs
- your_tits
- your_hair
- so_cute
- so_beautiful
- marry me
- fap_fap
- so_pretty
- we_all
- dont_forget
- this_girl
- right_in
- is_to
- she_will

**Male**
- you_are
- is_her
- does_she
- she_doesnt
- did_she
- is_she
- when_she
- she_is
- what_f_up
- welcome_to
- is_up
- are_on
- is_the
- of_the
- here_is
- link_to

**Female**
- the_game
- he_is
- you_want
- you_are
- if_you
- do_it
- it_is
- of_the
- will_be
- how_do
- you_get
- it_was
- is_the
- for_the
- what_is
- to_get
- in
- the
- did_not
- to_do
- with
- on_the
- that_was
- at_the
- would_be
Figure 4: Visualization of channel vectors
Figure 5: Gender preferences in channel selection. (a) Percentage of female channels among the channels that a user posted (among users who posted in at least 5 channels), (b) The same percentage among users who posted in at least 10 channels.

Figure 6: Visualization of user vectors using t-SNE
Figure 7: Cosine similarity skew