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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. Although online interaction shrinks social and geographical barriers, it is argued that social disparities, such as gender inequality, persists. For instance, online gaming communities have been criticized for objectifying women, which is a pressing question as gaming evolves into a social platform. However, few large-scale, systematic studies of gender inequality and objectification in social gaming platforms exist. 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. We find that female streamers receive significantly more objectifying comments while male streamers receive more game-related comments. This difference is more pronounced for popular streamers. We also show that the viewers' choice of channels is also strongly gendered. Our findings suggest that gendered conversation and objectification is prevalent, and most users produce strongly gendered messages.

Introduction & Background

Simone de Beauvoir (2012) said, "One is not born a woman, but becomes one," highlighting the idea that women are not free to make decisions about their lives but are 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 (Gill 2008). Such media continue to reinforce women as objects under the "gaze" of men (Holland, Holland, and Ramazanoglu 2004 01 15).

The Internet and the Web enable complex forms of many-to-many social interactions 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, gender bias effects the visibility of its users (i.e., females experience a "glass-ceiling" in Twitter) (Nilizadeh et al. 2016) and its dialogue (Garcia, Weber, and Garimella 2014; Fulper et al. 2015). Studies on image search engines (Kay, Matuszek, and Munson 2015) and Wikipedia (Hill and Shaw 2013; Wagner et al. 2015; Graells-Garrido, Lalmas, and Menczer 2015) also demonstrate persistent gender stereotypes and disparities.

Online gaming, however, has received little attention, although the advent of the Internet and of social media has transformed video games into genuine social activities (Kaytoue et al. 2012). 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 video games.

Traditionally considered a "boy's activity" (Cassell and Jenkins 2000; Su and Shih 2011), the culture of gaming communities has been accused of misogyny (Massanari 2015). Videos games themselves can be a medium that glorifies the objectification of women (Dill and Thill 2007; Burgess, Stermer, and Burgess 2007; Paaßen, Morgenroth, and Stratemeyer 2016). The online space of video games provides no respite from these inequities; ethnographic studies have reported 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 (Su and Shih 2011; Nardi 2010). In a study on a modern massively multiplayer online role-playing game, researchers reported that female gamers who "swap gender" and play male avatars not those who play female avatars achieve higher levels as quickly as male gamers do (Lou et al. 2013).

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. With one of the most popular of these platforms, Twitch, gamers can stream their gameplay and communicate with viewers in real-time. Any gamers, even non-gamers, can watch professional gamers' play all the time and engage with them. To give an idea of its popularity, Twitch had in 2015 a monthly average of 1.7 million broadcasters and half a million concurrent viewers (Twitch

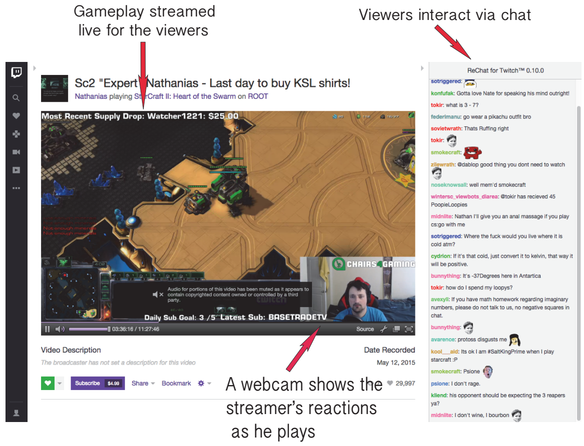

Figure 1: Twitch Channel Stream Interface

2015). 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 (McCormick 2013).

A sign of the success of e-sports is the establishment of professional gamers and related personalities. Some of these gamers, by broadcasting on Twitch, have garnered a level of fame and popularity that rivals that of many traditional celebrities. Central to the success of these individuals are their *channels* or *streams*. Channels facilitate communication between *viewers* or *users*, and streamers by providing *chat rooms* in which viewers can post *messages* to communicate with the streamers or with other viewers. Each channel has exactly one chat room. In general, the dynamics of a chatroom can vary widely between popular and less popular channels; for instance, chatrooms with messages rapidly scrolling by reflect the high rate of viewer postings in popular channels. Streamers can post in a chat room like any other viewer but often just share their *webcam feed* and engage directly with the audience. Fig. 1 shows the interface of a typical Twitch channel from the point of view of the audience. It includes a game stream, the webcam feed of the streamer, and the feed of its public chat room.

A channel is typically run by an individual streamer, but it can also be run by a group of streamers, an organization, or a channel aggregator. Streaming may be a major source of income for these entities. Potential sources of revenue include: holding game events, growing a base of subscribers, encouraging donations, playing advertisements, and having affiliate programs from sponsors. Thus, there exists a strong incentive for streamers to entertain and attract viewers. Browsing the list of public channels, one can not only find a wide variety of games but creative performance arts such as painting, music, and animation. Many streamers have their "main" game but play multiple games in their channels.

Twitch is an exemplar for the new, 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 (Dalsgaard and Hansen 2008). With this fundamental transformation in gaming culture where viewers and streamers both have the power to communicate and to be seen, our study investigates how gender inequality manifests in the Twitch platform. We ask the following research questions:

- *Do streamers receive gendered messages?* 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?

We believe that 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. This influence may have far-reaching consequences outside the domain of social media, for example by distorting beliefs about women in the real world (Behm-Morawitz and Mastro 2009). Additional contributions of this work include the novel application of an exploratory data analysis technique, which combines `t-SNE` dimensional reduction, `doc2vec` document embedding, and vector algebra. This methodology can be easily adopted in different domains.

Ethics Statement This study was deemed exempt by the Indiana University IRB (#1609276630).

Methods

Data and Terminology: Our data is comprised of all chat messages posted in public Twitch chat rooms between August 26th and November 10th in 2014 (76 days). There were 1.2 billion messages posted in 927,247 channels (1,375 messages per channel on average), by 6,716,014 viewers (190 messages per viewer on average). For each message, the following information was available: timestamp, author, channel, and message text. Author and channel are identified by screen name; for the channel, the name of the streamer.

Similar to other social media, the *activity* and *popularity* of Twitch channels are highly skewed. We define activity as the number of messages produced by each user and channel, and popularity as the number of users chatting in a channel. Fig. 2 shows that the distributions of these variables span several orders of magnitude. Such a heterogeneity may have strong effects in the language used in different channels. It has been observed that, as the rate of messages increases, messages become shorter and contain more emoticons (Nematzadeh et al. 2016). Since male streamers tend to be more popular on average than female ones, and more popular channels have a higher rate of chat activity, statistical estimates of language difference may be biased. To control for this potential source of bias, we match (Rosenbaum 2002) male and female streamers based on their channel activities.

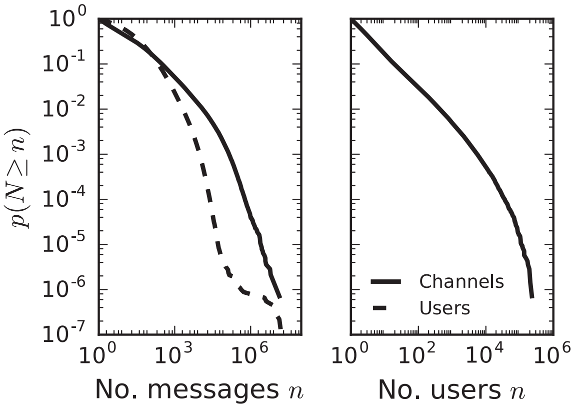

Figure 2: Activity and popularity on the Twitch chat. Left: distribution of the # of messages produced by each channel (solid line) and by each user (dashed line). Right: distribution of the number of chatting users per channel.

Our analysis is therefore based on a subset of 71,154,340 messages posted to the chat rooms 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 streamers who did not share their webcam. 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 $1,000$-$16,000$ in chat activity, and identified 101 female streamers.

Having found a sample of female streamers, we identified a matched sample of male streamers. 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, we narrowed our sample to streamers we could manually identify as male and who used English in their profile. From hereon, we refer to the top 100 channels for each gender as *popular* channels and the rest as *less popular* channels.

Statistically Overrepresented Words: As our first exploratory analysis, we detect unigrams and bigrams that are over-represented in either male or female streamers. To do so, we use log-odds ratios with informative Dirichlet priors (Monroe, Colaresi, and Quinn 2008). This 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 α. The log-odds ratio for word *w*, $\delta_w^{(i\text{-}j)}$ is estimated as:

$$\delta_w^{(i\text{-}j)} = \log \frac{y_w^i + \alpha_w}{n^i + \alpha_0 - y_w^i + \alpha_w} - \log \frac{y_w^j + \alpha_w}{n^i + \alpha_0 - y_w^j + \alpha_w} \quad (1)$$

Here n^i (resp. n^j) is the size of corpus i (resp. j), y_w^i (resp. y_w^j) is the count of word w in corpus i (resp. j), α_0 is size of the background corpus, and α_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,

$$\sigma^2(\delta_w^{(i\text{-}j)}) \approx \frac{1}{(y_w^i + \alpha_w)} + \frac{1}{(y_w^j + \alpha_w)}, \quad (2)$$

and thus a z-score:

$$Z = \frac{\delta_w^{(i\text{-}j)}}{\sqrt{\sigma^2(\delta_w^{(i\text{-}j)})}} \quad (3)$$

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 when detecting significant differences of frequent words without over-emphasizing fluctuations of rare words (Monroe, Colaresi, and Quinn 2008; Jurafsky et al. 2014).

Word and Document Embeddings: Although we rely on term frequency estimates for our exploratory analysis, for a finer characterization of the language of individual users and channels, we use representation learning (Bengio, Courville, and Vincent 2013). 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 using paragraph vectors (`doc2vec`) (Le and Mikolov 2014), which is a popular extension of `word2vec` embeddings (Mikolov et al. 2013). This joint embedding allows vector operations across documents and words, and has been argued to outperform other document embeddings in document similarity comparison tasks (Dai, Olah, and Le 2015).

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)—we chose the DBOW model because of its conceptual simplicity, efficiency, and reported superiority in performance (Dai, Olah, and Le 2015). We use an implementation of `doc2vec` available in the `gensim` Python library (Řehůřek and Sojka 2010). 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].

Pre-processing: To identify non-trivial gendered terms, we removed terms that obviously signal gender: "he," "she," "hes," "shes," "his," "her," "hims," "hers," "himself," "herself," "man," "woman," "bro," "boy," "sir," "dude," "girl," and "lady." In addition to these words, there exist *streamer-specific features* such as streamer names, nicknames, and custom emotes which are associated with a particular streamer and thus to their gender. We could not find a systematic method to filter out these words, and to avoid

[1] https://github.com/scnakandala/twitch-gender

bias due to incomplete knowledge of these terms, we decided to keep them in the corpus. It could be argued that, on one hand, inference on the basis of this information alone may be a threat to generalization. On the other hand, this information is inherently dynamic and the result of specific sub-culture. A model that identifies these features may be genuinely useful.

Gender Prediction: Prior work in the literature performs gender prediction, or detection, based on lexical (e.g., words, n-grams) (Bamman, Eisenstein, and Schnoebelen 2014), stylistic (Preotiuc-Pietro, Xu, and Ungar 2016), or syntactic approaches (Hosseini and Tammimy 2016; Johannsen, Hovy, and Søgaard 2015). Note that our task here is to predict the gender based *not on what they write*, but *on what they receive* from many viewers. Thus, the applicability of existing methods, particularly those that use stylistic or syntactic approaches, is limited. We also focus on lexical features, employing L2-regularized logistic regression on normalized document vector embeddings as well as a BoW (Bag of Words) model with 10,000 features obtained from TF-IDF vectorization (Aggarwal and Zhai 2012).

Results

Exploratory Language Analysis: We identify gendered terms with an exploratory analysis. Channels are grouped based on popularity and gender, producing four large "documents": 'popular male,' 'popular female,' 'less popular male,' and 'less popular female.' To remove noisy estimates and rare, ultra-specific jargon, we select terms that appear at least 100 times in at least 20 female or male channels.

We then extract all unigrams and bigrams from these documents and compute their log-odds ratio using Eq. 1. For the prior, background term frequency was computed on the *entire* Twitch dataset, and not just on the sample. The terms are then ranked by their estimated z-scores computed using Eq. 3. The 25 most *over-represented* unigrams and bigrams are selected and visualized in Fig. 3. For female channels, these are the ones with the largest z-score, while for male channels, these are the one with the smallest ones. We manually categorized unigrams and bigrams into four groups: *streamer IDs*, *game-related jargon*, *objectifying cues*, and *miscellaneous*. For IDs and jargon, we used information available on Twitch and other online forums. For the objectifying cues, we picked any term that matched either of the following two operational definitions: "language that reduce women to their body or appearance" (Langton 2009), or "objects to be owned or used" (Nussbaum 1995).

Looking at unigrams (Fig 3, left), popular channels display a strong contrast between genders. Game-related words are overrepresented in male channels, while objectification cues are strongly associated with female channels.

Less popular channels, however, do not display such a strong contrast, but show other interesting features. First, female channels feature words that signal social interactions, such as "hello," "bye," and "song" (the latter likely due to automated playlist requests). Second, the presence of the word "warning." This suggests that less popular female channels tend to have stronger moderation in place and are used more as a social gathering than a sporting event.

Bigrams (Fig. 3, right) display similar patterns. Among popular channels, female channels are characterized by terms about their physical appearance; male channels are instead associated with more game-related terms. Because several bigrams feature pronouns, we can appreciate some gender-specific behavioral differences between popular and less popular channels. In channels of popular female streamers, bigrams categorized as objectifying cues address the streamer directly via second-person pronoun. The non-objectifying ones, in contrast, use the third person, regardless of gender of the streamer.

This gender disparity does not hold when we look at less popular channels. That is, there is no trace of objectifying cues in female channels, and the second person is the norm. This observation suggests that popular channels see users behave much like as if they were watching a sporting event, but with a twist: objectifying language appears when the person being watched is a female. In less popular channels, instead, the communication gap between viewers and streamers is not only reduced; it is also neutral with respect to gender.

Analyzing Channels: To identify lexical features from female and male channels, we train document embedding models for our selected 400 channels. After preprocessing (see the *Methods* section), we train the `doc2vec` model. As noted, document and word vectors are trained jointly. Although a subset of the chat data is used, it is large enough to learn `doc2vec`. We visualize the vectors by applying `t-SNE`, a popular dimensionality reduction method based on manifold learning (van der Maaten and Hinton 2008). Fig. 4 suggests some clustered structure based on gender.

We then train two classifiers that predict the gender of a streamer. We evaluate the model by using 5-fold cross validation. The BoW-based model exhibits an accuracy of 74% (± 0.11%, 95% confidence interval) and a mean AUC of 0.80 in ROC curve for the holdout test set. Our `doc2vec`-based model obtains an accuracy of 87% (± 0.07%, 95% confidence interval) and a mean area under curve of 0.93.

As mentioned above, there are streamer-specific features that are associated to a specific channel (and thus to a gender). Therefore, it is crucial to examine the key features that are identified by these models. 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, and 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, body, relationships, and greetings, while male channels are characterized

Figure 3: Statistically over-represented n-grams in female and male channels Left: unigrams. Right: bigrams. Font size is proportional to the z-score.

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

Table 1: Channel classification learned features

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

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

by game-related words. Male channels are also associated with many uncommon words, suggesting that 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 affirmative.

Analyzing Individual Users: We turn our attention from *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. In particular, we examine whether the selection of which channels to watch and post to is associated with a given gender. We calculate for each user the percentage of their posts that are posted to the female channels in our sample of 400 channels. Of the 1,818,028 users who posted at least one message in our 400 channels, 93,898 of them (5%) also posted at least 100 messages.

We narrow down our user pool to this latter subset 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, those who posted exclusively in female or male channels—but not both—were 42,068. They are distributed as follows: 20,185 male-only and 21,883 female-only. Most of them has posted messages in popular channels (see Table. 2).

Let us examine the linguistic differences of this subset of *strongly gendered users*. As described before, the whole set of all chat messages of a given user is considered a document, and a vector-space representation of this document is obtained using `doc2vec`. Due to the computational over-

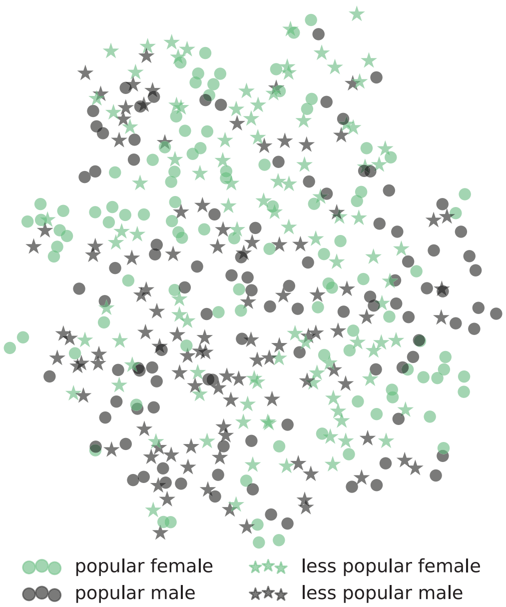

Figure 4: Visualization of channel vectors

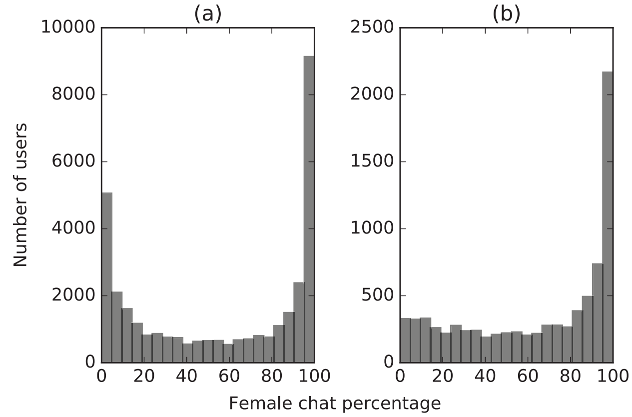

Figure 5: Gender preferences in channel selection. (a) Percentage of female channels among the channels that a user posted (among users who posted in at least 5 channels), (b) The same percentage among users who posted in at least 10 channels

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, kaceys, catcam, kaceytrons, objectify, poopbutt, objectifying
Kitty	kitty, kittyplaysgames, moonwalk, kittys, kittythump, kittyapprove, caturday, kittysub
Trick2g	trick, godyr, dyr, dcane, trklata, trkcane, trkhype
Mods (Moderators)	superfancyunicorn, tsagh, omeed, ironcore, tobes, snago, ara, moblord
Spanish	dividir, jajajaja, palomas, carajo, belleza, negrito, aca, peruano

Table 3: Representative words for the identified clusters.

head of our analysis (particularly `t-SNE`), we randomly selected 10,000 users (24%) and examine them closely. Of these, 4,802 are female-only viewers. 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 lexical contrasts. It also shows distinct clusters. We describe them by identifying strongly associated words. Specifically, given a cluster of n document vectors $C = \{d_1, d_2, \ldots, d_n\}$, we find every representitive word w that is close to many of the documents vectors, satisfying the following condition:

$$\frac{\left|\{d \in C | S_c(d, w) \geq s_{\min}\}\right|}{|C|} \geq f_{\min}, \tag{4}$$

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

We select eight clusters from the `t-SNE` map and label them with representative words, which are shown in Table 3. Analysis of Fig. 6 reveals interesting patterns. For instance, all representative words in what we call the "League of Legends (LoL)" cluster represent either a position (e.g. "junglers") or a character (e.g. "thresh") from that 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 the Spanish language and chat moderators. The terms in the "Mods" cluster are the IDs of users who are known as moderators for multiple channels.

To better understand the relationship between these gendered users and their language, we first pick pairs of terms identified from the exploratory analysis in Fig. 3. We pick an objectifying cue and a game-related term—for example, "points" and "boobs," which we identified from the "Statistically Overrepresented Words" analysis. We then calculate the cosine similarity between each word and the user document vectors to identify those vectors which are most similar to either 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). Two groups of users are clearly separated on the map. Interestingly, the eight user clusters we choose earlier tend to contain only one set of users. For instance, the "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 similar semantic contexts with the word "boobs." Indeed, Kaceytron is controversially known to brazenly ob-

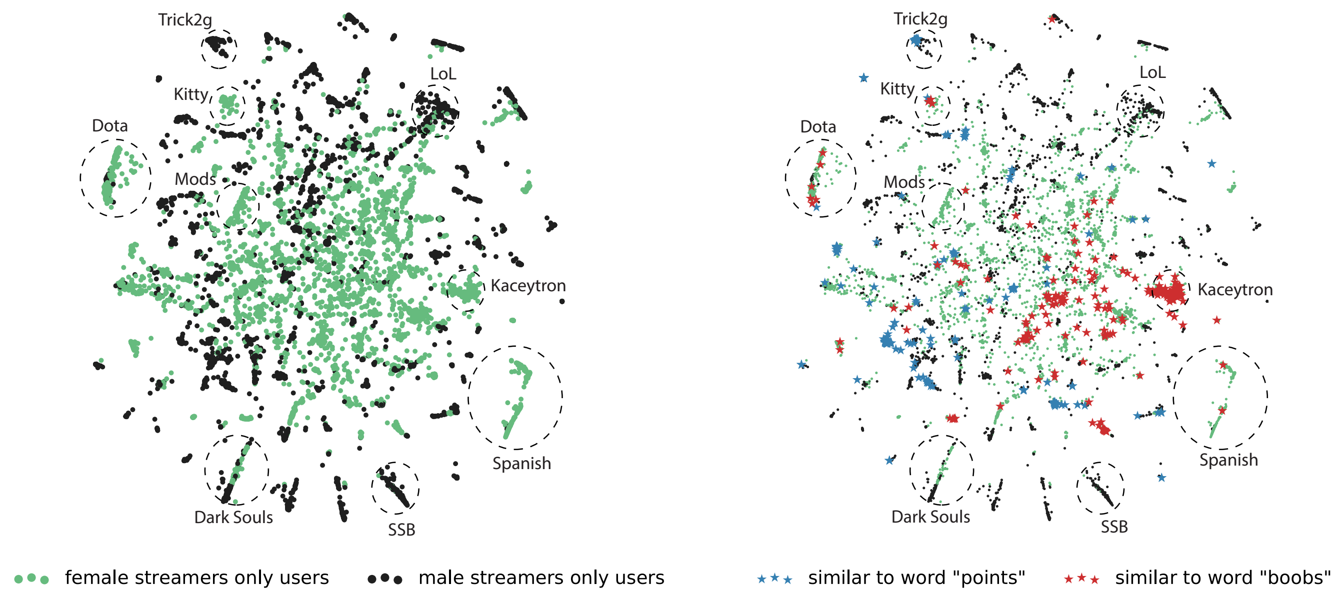

Figure 6: Visualization of user vectors using t-SNE

jectify herself in a sardonic manner (e.g. "attracting viewers with cleavage"); she is also famous for not banning anyone nor filtering any comments as well as directly responding to abusive comments (MostlyBiscuit 2015). By contrast, the "Trick2g" cluster, which we named after a streamer famous for his game commentaries, only contains users whose vectors are similar to "points."

Inspired by this clear clustering, we analyze how strongly gendered users are distributed along the spectrum of gendered vocabulary in the Twitch chat. We manually selected eight word pairs, each pair containing an objectifying cue and a game-related word identified from Fig. 3. 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 $\vec{v}_{g\to o} = \overrightarrow{w_o} - \overrightarrow{w_g}$. 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 $\overrightarrow{w_o}$ and a negative value suggests the user vector is closer to $\overrightarrow{w_g}$. The skewness in distributions for each gender (shown in Fig. 7) confirms our intuition. Messages of viewers who only post in female-streamer channels tend to share similar semantic contexts with words that signal objectification compared to users who post only in male-stream channels. In contrast, messages of those who post in male-stream channels tend to share similar semantic contexts 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 `doc2vec` features and one with BoW features. Using 5-fold cross-validation, BoW features achieve an accuracy of 96% ($\pm$ 0%, 95% confidence interval) and a mean area under curve of 0.99 in ROC curve, while `doc2vec` features achieve 88% ($\pm$ 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.

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

Table 4: Learned features for users with strong gender preferences.

However, feature analysis shows that much of the predictive power of the BoW model comes from the streamer-specific features discussed before: streamer IDs or custom emotes (see *Methods*). Table. 4 lists the most important features in the 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, captures more general terms and confirms the existence of objectification and gendered phenomenon.

Thus far, our focus has been on the majority of users, those who post only in male or female channels. We now turn to the rest of our user sample, those who post in channels of both gender. Because these users have less gendered preferences, at least in their channel choice, it could be that their language is also less gendered. To answer this question, we select a set of 2,734 users who posted an approxi-

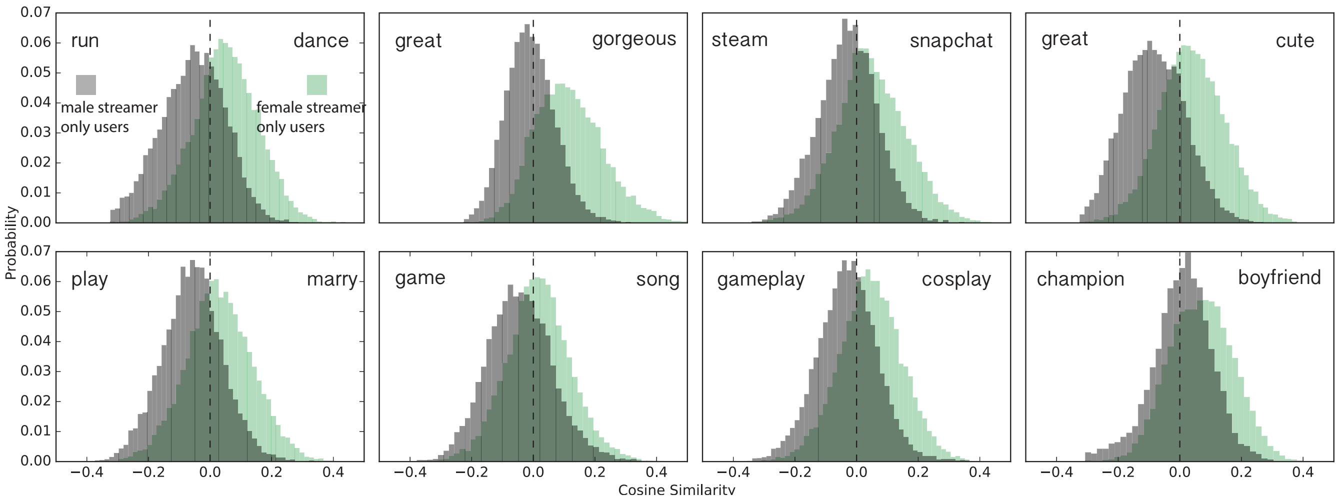

Figure 7: Cosine similarity skew

	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, fp, chopper	moe, nelson, hutch, abdou, coty, chris, arnie, mr, boogie, bbg

Table 5: Learned features for users with balanced gender preferences.

mately equal amount of messages in both female and male chat rooms (female chat percentage between 40-60%). We refer to these users as *balanced*.

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 room the message was written in. Similar to our 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% confidence interval). Surprisingly, the learned features, from both of these methods, are similar to the features found for the strongly gendered users (see Table. 5). This suggests that objectification is common even among the users who do not show clear gender preference in choosing channels. Thus, objectification behavior may not merely be limited to a niche user group but is a more wide spread phenomenon in Twitch.

Discussion

There are plenty of anecdotes that conversation in social game-streaming platforms like Twitch are gendered and objectifying for female streamers. Our quantitative analysis provides a systematic and comprehensive perspective to answering what role gender plays with online streamers and the conversation of their viewers in the gaming domain. Returning to the research questions we posed, our analysis on both streamers and viewers offers strong evidence that *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 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 play an important role, not only in terms of information overload (Nematzadeh et al. 2016) 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, user document embedding reveals the existence of user clusters consisting of famous moderators, indicating that strong, effective moderation is in place for many channels. Pronoun usage also changes depending on the popularity of channels; less popular channels are characterized by second-person pronouns, signaling more intimate conversation *between* viewers and streamers, while popular channels exhibit a pattern where viewers talk *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 priors and `doc2vec` was effective in unpacking the gendered nature of chat messages. `doc2vec` allowed us to look at words and documents in the same space and also performed better than BoW by learning features that are more contextual and general. This suggests that `doc2vec` may be more useful over BoW in settings where heavy data curation based on domain knowledge is essential. In addition, exploratory analysis utilizing `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 a parallel to models by Fu et al. (2016) that found questions posed by journalists to professional female tennis players objectified women, while questions posed to male players were game-related, and by Way et al. (2016), who found subtle gender inequalities in faculty hiring practices among universities of different rankings and career trajectories. Our methods can be generally applied to analyze the different user interaction patterns in any chat-based online platform.

Our analysis has several limitations. Most notably, we provide only a *static* picture of Twitch limited to questions about association rather than causal relationships. Although we can only surmise the causes of 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. Perhaps some women may feel they can only succeed in online streaming by giving in to the pressure of a gaming culture that normalizes or fetishizes the objectification of women. This vicious cycle may reinforce and spawn the structural problem of gender imbalance in online social gaming communities. If part of feminism's remit (Butler 2011) is to consider how both men and women 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 is a wide range of streamers—from those who play games without talking or chatting to those who actively engage with viewers through gaming events and small talk. 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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