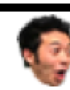
Chat Speed OP : Practices of Coherence in Massive Twitch Chat

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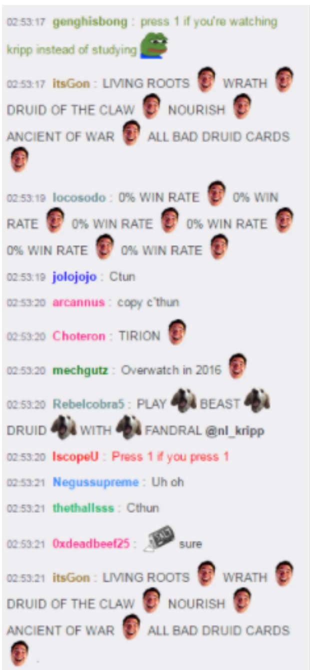
Abstract
Twitch.tv, a streaming platform known for video game content, has grown tremendously since its inception in 2011. We examine communication practices in Twitch chats for the popular game Hearthstone, comparing massive chats with at least 10,000 concurrent viewers and small chats with fewer than 2,000 concurrent viewers. Due to the large scale and fast pace of massive chats, communication patterns no longer follow models developed in previous studies of computer-mediated communication. Rather than what other studies have described as communication breakdowns and information overload, participants in massive chats communicate in what we call "crowdspeak."

Author Keywords
Twitch; chat; computer-mediated commuication; CMC

ACM Classification Keywords
H.1.2 Human Factors

Introduction
Launched in 2011, Twitch.tv is an online video-hosting platform where gamers live-stream their gameplay. The word twitch connotes "short," "sudden," even "convulsive," a fitting term for the rapid and seemingly incomprehensible discourse found in the massive Twitch chats for top games like League of Legends and Hearthstone that regularly draw more than 10,000 concurrent viewers [21]. Individual messages often have only a few seconds

Figure 1: Massive chat (TrumpSC's stream); 13 messages / 4 seconds.



of screen time before rushing out of view. Massive chats thus present unique circumstances for collective communication, as the number of concurrent viewers exceeds, by thousands, that of most Internet Relay Chat (IRC) channels or other chat spaces. Building on Hamilton et al.'s distinction between small and massive Twitch chats [5], we compared the two, finding that participants in massive chats developed a distinctive form of communication supporting large-scale interaction, or what we call "crowdspeak." Crowdspeak may appear chaotic, meaningless, or cryptic. However, we discovered "practices of coherence" that make massive chats legible, meaningful, and compelling to participants. By coherence, we simply mean that the chat makes sense to participants and is not experienced as a breakdown, overload, or other difficulty.

Chat has been a topic of academic research for decades, with early studies dating back to the 1970s [10]. These studies largely center on conversational modes of speech, where dialogue takes place in interspersed threads through which participants address specific others, either as individuals or groups [4, 5, 6, 7, 17, 26, 28]. A key concern in this research has been documenting the ways coherence is sustained or dissolved. For example, Greenfield and Subrahmanyam found that teen chat participants maintained conversational coherence by creating small discussion groups within larger chats, using visual cues, and making use of abbreviations. In particular, coherence was achieved by "establishing who is participating in a particular conversation and establishing what constitutes a relevant response" [4]. Though the technology used by Twitch is nearly identical to such systems, the massive chats we studied look quite different than what is conventionally considered "coherent"—massive chats are filled with non-sequiturs, verbatim repetition, variations on prior messages, blocks of text copied from elsewhere, and tiny messages that include only a few words or emotes. As conventional conversational coherence "breaks down" [5], participants achieve a different kind of coherence that prioritizes crowd-based reaction and interaction over interpersonal conversation.

We studied Twitch channels streaming the popular Blizzard Entertainment game, Hearthstone: Heroes of Warcraft. Twitch's Hearthstone section features a variety of prominent streamers such as Reynad, Kripparian, and TrumpSC, whose events attract upwards of 10,000 concurrent viewers. The game also supports small streamers such as Ryzen, Alliestrasza, and ZalaeHS, whose audiences range from around 100–2,000 viewers. Hearthstone thus presents an ideal opportunity to study differences in communication patterns by viewers of the same game, making it possible to examine whether and how communication differs by chat size.

To assess communication patterns, we observed and recorded small and massive chats between April and August 2016. We hypothesized that: 1) messages in massive chats would be shorter in length (reducing the time needed for input); 2) massive chats would contain less original content (making it easier to grasp meaning); and, 3) massive chats would contain fewer unique "voices," i.e., perspectives or stances. To test these hypotheses, we analyzed 50-message segments of text from five small chats (<2,000 viewers) and five massive chats (>10,000 viewers). We measured message length, amount of original content, and number of unique voices in each segment. We used linguist John Sinclair's theory of lexical items to define metrics for original content. Noting that words often hang together in meaningful combinations, Sinclair argued that the most important units of linguistic analysis are not words, but *lexical items*. Sinclair defined lexical items as "units of meaning" that may be words, but are often word pairs or groups, such as phrases like "the naked eye" or "diamond in the rough." [19]. We quantified original content by counting unique lexical items in each 50-message segment. We found that massive chats featured fewer

Figure 2: Small chat (ZalaeHS' stream); 16 messages / 111 seconds.

unique lexical items, i.e., less original content, which helped mitigate its rapid pace.

In massive and small chats we measured message length by counting the number of lexical items per message. We found that massive chat messages contained fewer lexical items on average, requiring less time for participants to input a message. We measured original chat content by counting the number of unique lexical items per 50-message segment. We found that massive chat segments contained less original content on average. Although we did not quantify how often rhetorical elements such as emotes and copypastas were repeated, through our collective 300 hours of qualitative work, and based on one author's extensive long-term participation in Twitch chat communities, we observed that there is a great deal of repetition and reuse of lexical items in massive Twitch chats. This repetition of familiar elements recalls the practice of bricolage, a concept from Lévi-Strauss's work [11]. Bricolage indicates opportunistic use and remixing of elements from a fairly small repertoire. Bricolage occurs in massive chats in the use and reuse of a limited set of lexical items. Some may be small variants on prior elements. Lexical items in the Twitch set include words, phrases, emotes, commands, and copypastas. Emotes are small digital icons, often a face or character. Copypastas are blocks of text repeated by participants through the "copy" and "paste" commands. They are frequently found in Twitch chat, but may originate in other sites or forums.

We drew from Trausan-Matu and Rebedea's work [22] to specify the voices in a segment of text. Based on Bahktin's work, Trausan-Matu and Rebedea argued that voices are not equivalent to individual participants, but represent shared viewpoints or stances [23]. Their work highlights how several individuals may join into a single voice, representing a common perspective or approach. Or, the inverse may occur, where the same individual adopts multiple voices, switching positions and roles as conversation unfolds. We define a shared voice as a communicational position that multiple participants adopt by adhering to a consistent viewpoint, syntax, or style of speech. Shared voices can be seen in chat when, for example, several participants repeat the same or similar emotes or phrases (Figure 1). We calculated the total number of voices per 50-message segment, finding that massive and small chats exhibited a comparable total number of voices, despite the fact that *massive chats had nearly double the number of individual participants*. This consolidation of voices in massive chats supports communication at scale.

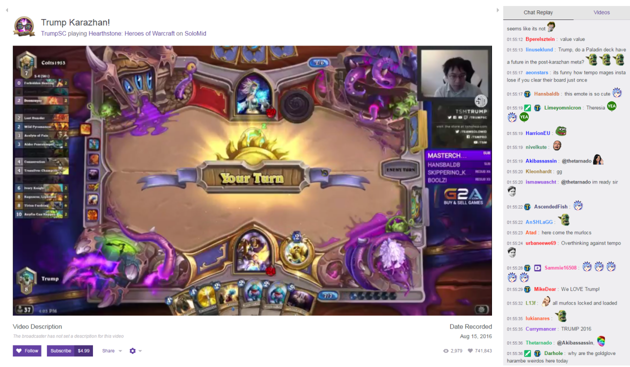
The communication practices we observed entail a shift away from individual, conversational speech towards collectivized crowdspeak which maintains coherence by reducing the total volume of meaningful content participants produce and process. The crowdspeak we observed did not attempt to build sequential threads of conversation in the manner of small scale chat discussed by Greenfield and Subrahmanyam [4] and others [5, 6, 7, 17, 26, 28]. Massive Twitch chats instead supported a playful form of participation more akin to chanting, clapping, or doing "the wave" in a large sports arena, where participation is enhanced by a crowd that not only watches, but speaks.

Large-scale text-based communication practices have implications for a still-growing internet. Global events such as political inaugurations, debates, and the Olympics are now routinely live-streamed. Due in part to the success of Twitch, many websites such as YouTube Live, Facebook Live, and Periscope offer real-time, concurrent chat to viewers alongside a stream's video feed. These technologies encourage crowdspeak as a form of active participation, potentially altering the way in which participation in major world events is viewed and experienced online.

Background

Twitch has increased in size and scope year by year, growing from 35 million unique monthly viewers in 2013 to 100 million in

Figure 3: Hearthstone: Heroes of Warcraft; streamer TrumpSC; gameplay left; TrumpSC's webcam feed top right; chat rightmost.



2014. Twitch supports nine billion+ chat messages annually [24, 25]. As a gaming-specific spinoff of the live-streaming platform Justin.tv, Twitch had eclipsed its parent platform by 2014 when it was acquired by Amazon.com [18].

That same year, game developer Blizzard Entertainment released Hearthstone, an online collectible card game set in their fantasy *Warcraft* universe. System-matched players play each other by casting spells and summoning creatures via cards with numerical values representing tactical information such as health and damage. Blizzard distributed closed beta keys to well-known Twitch streamers who built interest in the game by streaming themselves playing Hearthstone live before most people could play it at all [2]. By the time Hearthstone had been released to the general public, the game had already developed a dedicated audience on Twitch, with a few streamers devoting themselves to streaming Hearthstone full time. In 2016, Hearthstone was one of the top three games on Twitch by viewership and appears to be maintaining a top spot in 2017.

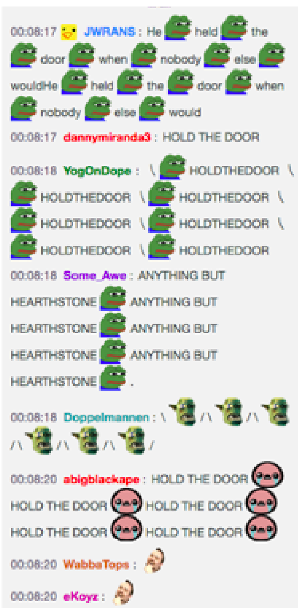
We refer to people who broadcast their gameplay on Twitch as *streamers*. Those who watch streaming events are *viewers*. *Participants* contribute to chat. Each streamer has a *channel* that goes online whenever s/he starts streaming. Viewers tune into channels to watch live *stream events* and can *follow* their favorite channels to be notified when the streamer is online. Streamers broadcast from a webcam alongside direct feeds of gameplay, allowing viewers to watch the game and the streamer simultaneously. Text-based *chat* occurs in the chat window beside the video display on the webpage. Most streamers split their attention between chat and playing the game, continuously responding to questions, reactions, ideas, or demands issuing from the chat (Figure 1). This setup allows *chat participants* to type and converse with one another in real time as the event unfolds.

By default, Twitch stream events are filtered by game, enabling viewers to select a game of interest and then pick from a panel of potential streamers to watch. Stream events are sorted by live viewership counts, which are displayed prominently below the stream title, permitting viewers to select a stream event based on its current popularity. Top professional streamers can earn six figure annual incomes [9] sourced from viewer donations, product sponsorships, advertising, and optional viewer subscriptions [3].

Related Work

As far back as 1978, scholars discussed how computer-mediated communication (CMC) affects human communication. Kochen [10] observed CMC as a "new linguistic entity with its own vocabulary, syntax, and pragmatics." In 1987, Rice and Love [16] predicted that CMC could "change the psychology and sociology of the communication process itself." In a computer conferencing study of Compuserv, they found that CMC "does not assume the importance of direct paths between [individual] users"—presciently anticipating the significance of the crowd in some forms of CMC (vs dyads or small groups). However, most re-

Figure 4: Massive chat (Reckful's stream); Patterns of communication may initially appear chaotic.



search has, to date, focused on the smaller scale spaces. For example, Schiano [17] found that in LambdaMOO, a popular MUD, "small, private, even exclusive social interactions were the rule, not the exception" with a good deal of interaction occurring "in the presence of one simultaneously active companion." Many studies continue to assume that the small group is optimal [5, 7, 14].

Herring [6] discussed "interactional coherence in CMC," arguing that, "It is possible for CMC to be simultaneously incoherent and enjoyable." Greenfield et al. [4] picked up the theme of coherence, finding that coherence was achieved in the teen chatroom they studied as participants clustered in dyads or small groups: "Many participants [in the large heterogeneous chat]...grouped themselves in dyads or smaller groups, with each group maintaining its own conversational thread." Weisz et al. [27] asked whether integrating text chat with video "enhanced or harmed" participant experience, concluding that "socializing around media is perhaps just as important as the media itself, and supporting social interactions during media consumption can significantly affect, and we hope enhance, the viewing experience." Studies such as these, and many continuing into the present, assume that "relationships" and participant self-expression and identity are critical for successful chat.

Werry [28] observed that within multi-stranded IRC conversations, language is "heavily abbreviated" with "syntactically-reduced forms, the use of acronyms and symbols, [and] the clipping of words." Varnhagen et al. [26] reported that instant messaging participants similarly developed "short cuts for expressing words, phrases, and emotions." Jones et al. [7] found that as chat size grew, the number of messages posted per participant declined, eventually reaching an asymptotic level at which the number of posters "remain[ed] constant." They reported a limit of about 600 messages per 20-minute interval: "Viewers can "absorb [up to] 30 messages per minute." They explained these findings as "constraints resulting from information overload." After the number of users (including both those who post messages and those who do not) exceeds about 220, "the community loses viability altogether" because people will not have their posts read and therefore will not post [7].

Jones et al. [7] noted that "while IRC is an old technology, it it is still used by millions of people around the globe on a daily basis" and is highly relevant to research. We concur, and find that contemporary studies of Twitch.tv are few but growing, contributing important understandings of changing patterns of communication. In a quantitative study of video game live streaming on Twitch, Kaytoue et al. [8] observed that most viewer traffic goes to a small number of Twitch streamers: "The top 10% [of] streamers concentrates 95% of all views, showing that audience attention is grabbed by a very small set of streamers." Hamilton et al. distinguished between small and massive Twitch chats, designating massive chats as those with more than 1,000 viewers. Hamilton et al. argued that increasing viewer size threatens a breakdown of "meaningful interaction," due to "huge, completely unreadable chats" [5]. At the same time, they acknowledged that massive chats are "compelling to some." Pan et al. [14] developed TwitchViz to help players and researchers examine chat behaviors, consistent with Jones et al.'s recommendation in 2008 that visual tools will be helpful. Given the rising numbers of viewers, "users are now often overloaded with information...mak[ing] it challenging for streamers to maintain an understanding of their own communities" [14]. Deng et al. noted the importance of Twitch.tv to industry, observing that 41 new games were pre-released on Twitch as promotion. They expect that "games will increasingly be designed with Twitch-like broadcast in mind" [2]. Building on Cheung and Huang's framework of spectator experiences, Smith et al. studied the YouTube Let's Play community observing that "the viewer her/himself [performs]...a very active and engaging role as part of the audience" [1, 20]. This study is not about Twitch.tv, but the authors commented that some Let's Players also use Twitch.tv to stream, arguing for the agentic quality of audience participation in both venues.

Methods

Figure 5: Terms and definitions.

PRIMARY METRICS
scroll rate: measured in lines of chat per time elapsed, as lines per second
message length: measured in lexical items per message
chat content: measured in number of unique lexical items per 50-message segment
voices: measured in total voices per 50-message segment
SECONDARY METRICS
word count per message: measured in words per message, where emotes counted as a word
unique word count per 50-message segment: measured in number of unique words per 50-message segment
participant count per 50-message segment: measured in the number of chat participants per 50-message segment

We used both qualitative and quantitative methods. One author has extensive experience playing Hearthstone, has been a long term participant on Twitch.tv, and provided contextual information about the game and chat practices. Authors without previous experience with Hearthstone learned to play the game during the initial weeks of the study.

We conducted 300 collective hours of observation watching Twitch chats and participating by playing Hearthstone between April and August 2016. We identified five channels whose streaming events commonly drew massive viewer counts and five channels whose streaming events commonly drew small viewer counts. As our primary intent was to understand massive chats, small channels were included to provide a comparative point of reference. From May 18 to August 19, 2016, we collected two 50-message segments from each channel, for a total of twenty 50-message segments. 50-message segments were large enough to observe patterns, but not so large as to be intractable for the necessary hand coding. We analyzed the segments in researcher pairs or triads to avoid skewing the results toward the potential biases of a single coder. Streaming events lasted from three to seven hours. Often as participants joined chat, they greeted the streamer and others, regardless of whether they continued to participate. To allow the chat to stabilize to those actively participating, we collected 50-message segments 90 minutes into an event.

Within our 50-message segments, we used four primary metrics to measure chat: 1. scroll rate; 2. message length; 3. chat content; 4. voices. Scroll rate was measured in lines of chat per time elapsed, as lines/second. Message length was measured in lexical items per message. Chat content was measured in number of unique lexical items per 50-message segment. Unique lexical items were counted as they first appeared in each segment (see rows 2 and 3, Figure 6). Voices were measured in total voices per 50-message segment. We also used three secondary metrics: 1. word count per message; 2. unique word count per 50-message segment; 3. participant count per 50-message segment. These secondary metrics helped interpret the primary metrics, as will be described in Findings (see Figure 5).

Figure 6: Example Coding Activity; 6-message segment.

#	Message	Lexical Items / Msg	Unique Lexical Items / Segment	Voices	Notes
1	Top Deck	1	1	1	Idiom
2	Combo	1	1	1	
3	Go Combo	2	1	0	
4	Its pretty card dependent	4	4	1	
5	Faceless Shambler is actually great in unicorn priest thanks for the idea :)	11	11	1	Faceless Shambler is a proper noun, name of card; unicorn priest is name of deck-type
6	Did he put 2nd earth shock in already?	8	7	1	Earth Shock is card; we counted "?" as a lexical item.
		Average / Msg: 4.5	**Total: 25**		

Findings

Our study revealed that massive chat participants styled their communication around three interrelated practices of coherence: *shorthanding*, *bricolage*, and *voice-taking*. Shorthanding is the contraction of text into a smaller space. Bricolage is the recombining of elements from a small repertoire. Voice-taking is the adoption of shared viewpoints, perspectives, or mannerisms. Shorthanding, bricolage, and voice-taking were intertwined; we delineate these three practices in our analysis in order to highlight how each produced coherence in massive chats. We believe that these three practices help explain why massive chats consistently attract large audiences and do not seem to produce

Figure 7: Twitch emotes and their meanings.

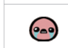
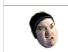
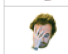
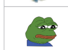
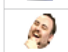
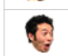
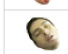
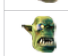
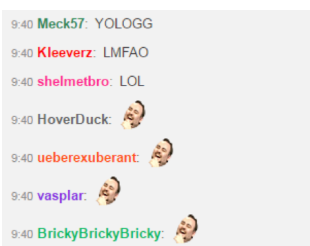
Emote	Name	Meaning
	BibleThump	sadness
	copyThis / pastaThat	copy / paste
	DansGame	disgust
	FailFish	disappointment
	FeelsBadMan	pity
	LUL	laughter
	PogChamp	amazement
	ResidentSleeper	boredom
	SMOrc	blunt / brutish

Figure 8: Massive chat (nl_Kripp's stream); YOLOGG



troubling communication breakdowns, instead constituting a different kind of communication at scale, i.e., crowdspeak.

In massive chats, fast scroll-rates and high participant counts created conditions where an individual message enjoyed only a small amount of screen time, and an individual participant's contributions formed only a small part of the entire chat content. Massive chats had an average of 47 participants per 50-message segment, compared to 25 participants in small chat segments (rounding for simplicity). Massive chats flowed by at a considerably swifter pace than small chats, with 1.74 lines/second in massive chats compared to .27 lines/second in small chats.

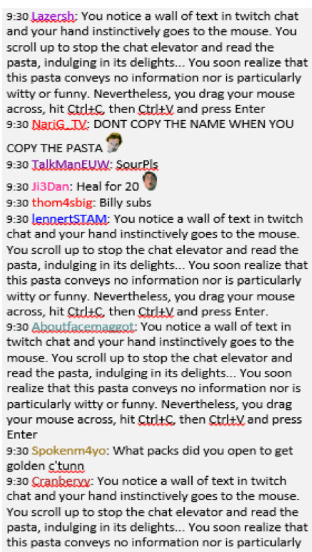
Shorthanding: Our first hypothesis, that massive chat messages would be shorter, was supported. Messages in massive chats contained fewer lexical items. Massive chat segments contained an average of 3.0 lexical items per message while small chat segments contained an average of 5.5 lexical items per message. Counting lexical items allowed us to differentiate between messages that may have had more or less semantic content; for example, messages containing a single emote versus messages with text extending to the end of the line. Lexical items allowed us to analyze pictorial messages where meaningful units were defined by images rather than words.

Metrics such as number of words and line length (which we also counted) seem like they would be good indicators of message length. But they proved inadequate for our analysis as they did not accurately reflect the structure of utterances in massive chats. For example, many messages were image-based, including ASCII art and emotes that are not typically considered words. There was no difference in average word count per message; both massive and small chats averaged six words per message (rounded). Line count per message also was imprecise; it did not distinguish between messages that filled part of a line versus all of a line. In an environment where messages containing a single word or emote can be as meaningful as longer phrases that might fill an entire line, we found lexical items to be a more useful metric.

Shorthanding occurred in the form of acronyms, abbreviations, emotes, and single word commands. These forms reduced the number of lexical items per message. For example, "!uptime" was a frequently used command answered by a chatbot that replied with the time the current stream event had been live. This command allowed participants to circumvent a lengthier, back-and-forth dialogue, reducing the number of lexical items needed to query and convey the event's uptime. Likewise, the command "!deck" anticipated and mitigated a dialogue that would have required more lexical items in order to procure information regarding commonly used card decks.

Other forms of shorthand worked because they relied on insider knowledge and references that allowed brief but vivid utterances. For instance, "Yogg-Saron, Hope's End," a popular card used by many Hearthstone streamers, casts a series of random spells at random targets, resulting in an infamous ability to either win or lose the game in spectacular fashion. The card, often simply called "Yogg," has become associated with the phrase YOLO (You Only Live Once), with some streamers shouting "YOLO" in anticipation of the card backfiring. This reference has been further developed into the acronym "YOLOGG" (Figure 8), which succinctly combines YOLO and Yogg-Saron, invoking the spectacle and randomness of Yogg-Saron without the need to explain it. These evolving layers of meaning provide complex shorthand references that may be specific to the game in question, to the streamer, to Twitch, or even to current world events. For example, during the time of our observations there were joking references to Harambe, a gorilla at the Cincinnati Zoo who was killed by a zoo worker when a 3-year-old boy climbed into the animal's enclosure. Comments such as "RIP HARAMBE BibleThump" appeared in chats after the playing of Hearthstone cards that featured a monkey or gorilla. While shorthand is not unique to mas-

Figure 9: Massive chat (nl_Kripp's stream); Copypasta about copypasta.


9:30 Lazersh: You notice a wall of text in twitch chat and your hand instinctively goes to the mouse. You scroll up to stop the chat elevator and read the pasta, indulging in its delights... You soon realize that this pasta conveys no information nor is particularly witty or funny. Nevertheless, you drag your mouse across, hit Ctrl+C, then Ctrl+V and press Enter
9:30 NariG_TV: DONT COPY THE NAME WHEN YOU COPY THE PASTA
9:30 TalkManEUW: SourPls
9:30 Ji3Dan: Heal for 20
9:30 thom4sbig: Billy subs
9:30 lennertSTAM: You notice a wall of text in twitch chat and your hand instinctively goes to the mouse. You scroll up to stop the chat elevator and read the pasta, indulging in its delights... You soon realize that this pasta conveys no information nor is particularly witty or funny. Nevertheless, you drag your mouse across, hit Ctrl+C, then Ctrl+V and press Enter.
9:30 Aboutfacemaggot: You notice a wall of text in twitch chat and your hand instinctively goes to the mouse. You scroll up to stop the chat elevator and read the pasta, indulging in its delights... You soon realize that this pasta conveys no information nor is particularly witty or funny. Nevertheless, you drag your mouse across, hit Ctrl+C, then Ctrl+V and press Enter
9:30 Spokenm4yo: What packs did you open to get golden c'tunn
9:30 Cranberyy: You notice a wall of text in twitch chat and your hand instinctively goes to the mouse. You scroll up to stop the chat elevator and read the pasta, indulging in its delights... You soon realize that this pasta conveys no information nor is particularly

sive chats [26, 28], its heavy use made for shorter messages in rapidly moving chat, allowing colorful participant responses to gameplay, Twitch, or broader cultural events.

Bricolage: Our second hypothesis, that massive chats would contain less original content, was supported. We found that massive chats included less unique content per 50-message segment. There was an average of 85 unique lexical items per segment in massive chats, compared to 169 in small chats (rounded). Our qualitative observations indicate that frequent repetition of lexical items in massive chats explains this striking halving of original content.

We characterize the practices at work in this reduction of unique content as "rhetorical" bricolage. Lévi-Strauss identifies bricolage as the practice of recombining a small set of resources-at-hand (such as known characters, tropes, and images) to construct collective narratives [11]. Chat participants practiced bricolage by recombining emotes, stock phrases (e.g., the Twitch phrase "top deck" or the popular phrase "drop it like it's hot"), and copypastas.

Emotes were common lexical items in Twitch bricolage. Participants' reactions to the streamer's gameplay often consisted of single emotes or emote-word combinations. Different emotes were associated with different reactions. Rapid repetition of the same emotes often occurred, such that streamers could quickly glean a sense of chat sentiment and reply accordingly. For instance, a string of PogChamp messages indicated amazement at an impressive play or situation, whereas LULs constituted laughter at the streamer's mistakes or bad luck. Participants' use of a shared emote lexicon led to a great deal of repetition (and thus less original content) in massive chats. We did not observe such heavy use of emotes in small chats.

Copypastas are exemplars of bricolage in their referencing, reusing, and/or remixing of previous elements of chat content. They tended to follow a formula, but a flexible one, in which participants could combine multiple copypastas or add custom elements. Each copypasta was either repeated verbatim or constructed with small, often playful variations on a previous copypasta. For instance, in Figure 9, several participants repeated a copypasta that commented on the experience of propagating copypastas, parodying participants "instinctively" copying and pasting in massive streams, with an ironic nod to the "pasta that conveys no information nor is particularly witty or funny." Copypastas were remixed to suit specific contexts. A common copypasta was "ONE MORE (LUL) AND I'M OUT." During a Kripparian event, several variations on this copypasta occurred:

"ONE MORE OUT AND I'M (LUL)"
"ONE MORE (LUL) AND YOGG IS DONE"

The content of individual copypastas became less important than the patterns of serial messages, producing coherence through reduction of original content.

Voice-taking: Our final hypothesis, that massive chats would contain fewer unique voices, was not supported. Total voice counts were comparable in chat segment sizes. However, when we analyzed voices as a ratio of total participants to voices, there was a clear asymmetry, with an average of 29 unique voices to 47 participants (rounded) in massive chats, and an average of 26 unique voices to 25 participants in small chats. With nearly twice the number of participants in massive vs small chats, the similarity in voice count is notable.

While participants in both chat sizes at times used their own voice in their messages, the lower ratio of voices to participants showed that massive chat participants more often adopted a voice from a collective repertoire. For example, SMOrc (pronounced "S M orc") is an emote associated with a common voice. When participants adopted SMOrc's voice, they tended to use a certain syntax and style, e.g., typing in all caps with simple

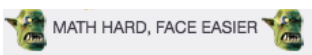


Figure 10: Massive chat (Zetalot's Stream): SMOrc advocates attacking the opponent directly in the "FACE," rather than calculating out the gameplay consequences.

sentence structure. Not only does SMOrc shun the use of grammar and lowercase letters, he also shuns advanced game tactics and tactful expression. As a voice, SMOrc is recognized and shared across multiple Hearthstone channels, an in-joke among participants. SMOrc's entire "philosophy" can be summed up in his quote "MATH HARD," referring to the basic mechanics of Hearthstone where every card has numbers associated with its ability to perform offensive or defensive functions. The use of SMOrc and similar emotes requires, and signifies, membership in the Twitch Hearthstone community. Speaking as SMOrc obscures the participant's voice behind a pugnacious Orc's shouts, producing coherence only because participants and viewers are in the know about gameplay, the streamer, and the semantics of the emote.

Some emotes produced voices of a more general nature. For example, LUL did not impose a specific grammar or subject matter but was always laughing in response to the misfortune of another, often the streamer. FeelsBadman consistently expressed pity for oneself or another. These emotes qualified as voices as they adhered to a consistent viewpoint, rather than consistent syntax. Not all emotes qualified as voices, however. BibleThump (sadness), FailFish (disappointment), and Resident Sleeper (boredom), for example, often simply served as a sort of punctuation to lend a tone to a message (much like an exclamation point).

Some voices did not include emotes, instead maintaining coherence through shared syntax or viewpoint. One example is "BUILD THE WALL" messages in TrumpSC's streams, referencing then-Republican presidential candidate Donald Trump. The resonance of this voice was unique to TrumpSC's streams because of the shared name with Donald Trump (TrumpSC's name has no actual relation to Donald Trump, referring instead to trump suits in card games). These messages, and variations like "BRING THAT WALL ONLINE," provided comical commentary that occurred when TrumpSC created defensive lines with his creatures during a game. Other messages like "Make priest great again" were a reaction to TrumpSC playing a Priest card-deck, in light of a common opinion among players that it was the worst class in the game. These voices allowed a shared, mock-political voice to emerge, styled around the distinctive syntax and phrasings of Donald Trump. This example showed a clear convergence of mannerisms, speech, and tone among some participants in massive chats, where shared voices were adopted from both Twitch-specific events and mainstream culture.

Discussion

Although we have drawn extensively from Hamilton et. al.'s work, one of our key conclusions differs in that we suggest that massive chats can be examined as successful communication spaces in their own right rather than as failing communities. Hamilton et al. argued that massive chats "destroy the potential for communities to form through participation" [5]. But the very popularity of these streams, with their huge viewership numbers, trouble this characterization. We argue that analyzing massive Twitch chats by taking smaller chats as a benchmark is precisely what obscures the coherence of massive chats. Rather, we found that massive chat participants deployed a consistent set of practices that allowed communication to continue at scale.

We focused on understanding texts that may appear incomprehensible to the average reader but are, in fact, the productions of a rich insider culture that draws from gaming, and well beyond, to many internet and popular culture sources. We observed that crowdspeak relied on tacit references, in-jokes, and acquired fluency. Crowdspeak was made possible by a vibrant community of chat insiders familiar with a specific, outwardly-obscure set of symbols, commands, and modes of speech. The presence of insiders mirrors Hamilton et. al.'s finding that small Twitch chat communities involve a small set of "regulars" who structure the conversation [5]. In massive chats, these model participants appear as a collective, recognized through adoption of shared references, lexicons, and speech patterns. Other studies have noted the importance of regular, known contributors to small chat communities [15], a notion based on Oldenburg and Brissett's original work on "third places" [12, 13]. Our observations suggest that in massive chats, regulars may not always be "known," but their contributions are no less vital.

Previous researchers have found or assumed limits to meaningful participation in chat contexts with a high number of participants. For example, Pan et. al. [14] developed the TwitchViz tool specifically to cope with a perceived information overload in massive twitch chats. Jones et. al. [7] described limits of IRC chat. However, our results suggest that chat contexts can spawn practices and content that call into question a ceiling at which breakdown or overload must always occur. In their treatment of third spaces, Oldenburg and Brisset [13] described the importance of a "conversational style" where everyone seems to speak "just the right amount." This "right amount" is essential to the sociability of the spaces [13]. We suggest that a Twitch-specific " right amount" of speech was occurring in the chats we studied, and that different chat contexts can have their own proper measure of rate and level of participation.

Our approach of deploying quantitative analysis of practices alongside close ethnographic readings of texts may be useful in analyzing crowdspeak as massive chats become more common. By using lexical items and voices as primary metrics of analysis, rather than words and participants, we were able to provide insight into modes of collective communication that may not rely on conversational norms of turn-taking, repair, or topical consistency. Rather, we observed that massive Twitch chats had their own alternative communicative patterns and practices. We believe such alternatives are exactly what some of the earliest scholars of digital communication pointed to when they noted that computer-mediated communication had emerged as a "new linguistic entity with its own vocabulary, syntax, and pragmatics" [10], and that CMC should "not assume the importance of direct paths between [individual] users" [16]. We note that participation in massive Twitch chats is less about individual identity and self-expression than it is about entering and engaging with a crowd, a topic worthy of continuing research. The crowd has historically attracted the notice of psychologists, sociologists, and philosophers, including Freud, Durkheim, Sartre, Kierkegaard, and Canetti, whose theories and ideas can inform future work. Our own future research, for example, might explore potential connections between crowdspeak and the myths and rituals of crowds.

Conclusion

Due to the rapid growth of live-streaming platforms like Twitch, YouTube Live, and Facebook Live, chat sizes have exploded. As Kaytoue et al. [8] remind us, most viewer traffic on Twitch goes to a few streamers, concentrating 95% of all views into a few massive channels [8]. Our research suggests that crowdspeak may provide an engaging and coherent communicative form in these growing online environments. Future research might examine the extent to which the morphology of crowdspeak may be affected by factors such as platform, primary language, streamer, topical focus, and many other factors. The crowd is on the rise, and researchers should be poised to attend to emergent forms of large-scale engagement and discourse, and their potential contributions to public life and digital media.

 END NOW 

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