Exploring Online Video Watching Behaviors

Frank Bentley
Yahoo/Verizon Media
Sunnyvale, CA
fbentley@verizonmedia.com

Max Silverman
Yahoo/Verizon Media
Sunnyvale, CA
maxsilverman@verizonmedia.com

Melissa Bica
University of Colorado, Boulder
Boulder, CO
melissa.bica@colorado.edu

ABSTRACT

Laptop and desktop computers are frequently used to watch online videos from a wide variety of services. From short YouTube clips, to television programming, to full-length films, users are increasingly moving much of their video viewing away from television sets towards computers. But what are they watching, and when? We set out to understand current video use on computers through analyzing full browsing histories from a diverse set of online Americans, finding some temporal differences in genres watched, yet few differences in the length of videos watched by hour. We also explore topics of videos, how users arrive at online videos through referral links, and conclude with several implications for the design of online video services that focus on the types of content people are actually watching online.

CCS CONCEPTS

• **Information systems → Multimedia streaming**; *Video search*; • **Human-centered computing** → *Empirical studies in HCI*.

KEYWORDS

Video; Streaming; Mid-Scale Studies; YouTube; Netflix

ACM Reference Format:
Frank Bentley, Max Silverman, and Melissa Bica. 2019. Exploring Online Video Watching Behaviors. In *Proceedings of ACM International Conference on Interactive Experiences for TV and Online Video (TVX 2019), June 4–6, 2019, Manchester, UK*. ACM, New York, NY, USA, 10 pages.

1 INTRODUCTION

There are currently many ways that users can stream video content to their computers. Professional television content is available on websites from individual networks (such as HBO or CBS), from websites of cable providers (such as Comcast Xfinity or Verizon Fios), or from over the top (OTT) solutions that go around networks and carriers (such as Netflix and Hulu). In addition, vast video content libraries are available to stream from online video sites such as YouTube or Vimeo. This gives users a great deal of content choice, compared to watching traditional linear television, yet little work has explored how users engage with all of these different sites on their computers.

Existing work has identified laptop and desktop computers as devices frequently used for video streaming [10] and rewatching [2]. Mann et al. [10] found that overall the computer is the second most preferred device (after the television set) for watching video content, with 38% preferring it over all other devices to watch TV and movies, 23% preferring it for watching sports events, and the majority (54%) preferring it to watch short video clips, such as YouTube. Users frequently watch content on computers from their beds or while another person in the home is watching something on the main television set [12].

However the existing literature mainly focuses on specific streaming sites, studying Netflix use or YouTube watching, and does not explore how users engage with the wide variety of video streaming sites that are available at once, including temporal differences in use or how multiple sites are used together or separately within a session. Despite the common nature of this activity, there is much we do not know about user behavior with online video on desktop and laptop computers.

We began this work with several research questions:

(1) How many different video services are users engaging with on their computers? Do people stick mostly to one service, or do they subscribe to a many different ones? Are these primarily networks or online-only streaming sites?
(2) What types of video content do users watch on their computers, in terms of length and topic/genre?
(3) What temporal patterns exist in watching video on computers? Are there differences by hour of day or day of week in the types or durations of content that people watch?
(4) How do users arrive at specific video content that they want to watch? Is it through links from other sites or

TVX 2019, June 4–6, 2019, Manchester, UK

through browsing on a video portal. Does this vary by service?

To answer these questions, we gathered full web browser logs from 174 diverse American participants, averaging 138 days of use per participant. We then explored the use of 20 different video sites in these logs to more broadly understand online video watching behaviors in the US population. We will set this work in the context of previous studies, then explain our research methods, explore answers to our research questions, and then discuss what this means for online video services and implications for the design of new services or features for desktop video streaming.

2 RELATED WORK

Watching online video has been increasing in popularity over the years, compared to traditional means of watching linear broadcast content. As of June 2018, 66% of U.S. households had purchased access to a subscription-based video on demand service (e.g. Netflix, Hulu, Amazon Prime) [15]. In addition to having large libraries of video content available, users have highly positive perceptions of these online services due to the added convenience of choosing when and where content is watched [19], not being restricted to a traditional television set and fixed-line, wired connection.

Watching Video on Computers

Given this new freedom of device for watching professional video content, surveys have shown that laptop and desktop computers are commonly used [10], and also preferred among many users compared to using a mobile phone to watch video [18]. Computers are also frequently used over television sets due to having greater access to various content through a web browser with fewer DRM or device restrictions and the ability to consume such content on demand at any time [11].

Rigby et al. [18] asked users in a lab to choose a Netflix movie to watch, which was split into multiple sessions that were randomized across devices (4.5 inch phone, 12-inch laptop, and 30-inch monitor). They found that watching a movie on a laptop or monitor resulted in greater immersion with the movie than watching on a smartphone, but there was no difference in immersion between the laptop and the larger monitor. Similarly, a diary study conducted with households in the UK that watched more than five hours of video a week [19] found that mobile viewing of video content was regularly seen as not enjoyable and avoided if the situation allowed it. Additionally, they found that while users had a stated preference for watching on-demand content on a television, a computer was still the most common device used.

Separate analysis from Rigby et al. indicated that the most common time to start watching on-demand video was late at night between 9-11PM [17]. Additionally, among this sample, the majority (69%) of viewing sessions were less than one hour, with only 12% of sessions over two hours in length. However, other research has shown [19] the length of viewing sessions differs based on whether the on-demand service typically hosts short- (e.g. YouTube, Vimeo) or long-form content (e.g. Amazon, Netflix). Sessions on short-form sites averaged about 42 minutes whereas sessions on long-form sites averaged 1 hour and 21 minutes.

Watching YouTube Videos

Cheng et al. [9] scraped over three million unique YouTube videos in 2007 and analyzed these videos on various dimensions, including the category assigned to the video on YouTube. They found that the three most common categories of videos were music (23%), entertainment (18%) and comedy (12%). In 2013, a similar process of data collection was conducted by Che et al. [8]. They found in 2013 that the music (23%) and entertainment (16%) remained the two most common categories, followed by gaming (8.5%) due to the decrease in comedy videos (12% in 2007 to 6% in 2013).

A separate 10-year analysis from 2006 to 2016 [6] focused on YouTube channels versus videos found that over this period, the number of music and entertainment channels that were created decreased (Music from 18% to 2%, Entertainment from 14% to 2% in 2016). On the other hand, the number of People & Blogs channels created rose dramatically from 13% of new channels in 2006 to 74% of new channel creation in 2016. Gaming channels saw a similar increase from 6% in 2006 to 12% in 2016. Additionally, this analysis found that the top 3% of YouTube channels from 2006 to 2016 accounted for 85% of all video views. These changes were quite dramatic, and we were interested to see if these trends continued or changed since 2016.

Bartl [6] found that that older videos had significantly more video views than more recently uploaded videos on YouTube. In 2006, it was found that the median number of views per video was over ten thousand, which became less than one thousand views in 2012, and less than one hundred median views in 2016[6]. As more YouTube content was posted each year, each new video was viewed less often.

In 2007, 98% of YouTube video lengths were 10 minutes or shorter in duration, due to YouTube's strict restriction on length [9]. In 2010, YouTube's default video upload length became 15 minutes [13]. A few months later, YouTube began to offer easy-to-follow verification instructions to increase the limit to 12 hours [20]. In 2013, Che, Ip and Lin [8] found that only 2.6% of all videos fell beyond 11.7 minutes, with Gaming and People & Blog videos leading to part of that increase. With the finding that both Gaming and People &

Blogs channels continued to increase as of 2016, it is also important to understand whether that has resulted in users' watching longer YouTube videos.

Binging Video Content

Across all of these video platforms, the concept of binging video is common. While there is no universally agreed upon definition of binge-watching, a Netflix survey indicated that the majority of consumers define binge-watching as watching the same show for 2-6 episodes within a single sitting [14]. Binging on-demand video, as referred to in the present day, has its roots in Netflix's choice to release entire seasons of their original content at once. In 2013, when Netflix released the 4th season of Arrested Development, it was found that 10% of the show's viewers watched all 15 episodes within twenty-four hours of its launch [1]. As binging TV or related video content has become more common across users, a number of researchers have attempted to understand the motivations behind such behavior.

Pittman and Sheehan [16] conducted a factor analysis to understand these motivations, both in the moment and when planning ahead to binge watch a show. Through a factor analysis of 27 potential statements grouped into five factors, a user's level of engagement was the greatest factor in predicting both current and future binge-watching behaviors and the only factor that predicted the amount a user watched a show [16]. The statements within the engagement factor included that the show was more interesting to binge, the show being very entertaining, feeling more engaged with the show and characters when binge-watching, and being able to follow the less prominent story lines within such show.

With the growth of these large online content libraries, and series syndicated from cable to online streaming, rewatching older videos has become more common Bentley and Murray [2] found that 79% of users in their sample rewatched videos in the past week, and 92% did so in the prior month. Some of the main motivations for doing so included rewatching the video content with others to share or see others' reactions, rewatching to change or replicate a mood, or for nostalgia purposes. Additionally, they found that only 26% of the top rewatched content matched the types of content that users most frequently watch on television (e.g. reality, sports, news, music). For shows with in-depth stories and characters, 41% were re-watched on a computer versus only 8% on a mobile phone.

This related work has shown how online video behaviors have quickly changed in the past and highlighted the need for updated work in this area. While many studies have been performed on particular services in the past, we were unable to find a study that focused comprehensively across video services watched on computers. With this desire to explore cross-service viewing and identify changes since much of this prior work was conducted, we set out on our study.

3 METHODS

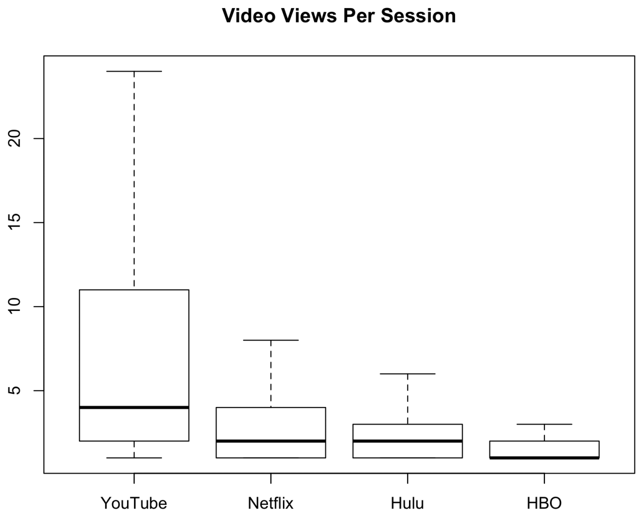
In order to broadly understand how people are consuming video content on the web, we collected a set of complete web browser histories from the personal computers of a diverse set of Americans. Participants were recruited on Amazon Mechanical Turk. After agreeing to participate, users were directed to an online survey which provided a detailed explanation of the data we were collecting and why, followed by instructions for how to find one's own browser history file (for either Chrome or Firefox) stored locally on their computer. The files contained a timestamped entry for each webpage viewed in either the last 3 months (Chrome) or since the user first started using the browser (Firefox), in addition to the URL and page title.

We paid participants $5 for their browser history files, and received valid data from 174 participants, totaling nearly 9.5 million unique page views over an average of 138 days of history per participant. Our incentive amounted to an average $60/hour wage and is in line with existing research that shows browsing history being valued at about the price of a Big Mac [7]. These participants are representative of the general US adult population in terms of age (18-72), gender (49% female), and household income (median $50k), and reside in 39 distinct US states. Previous studies have shown that MTurk samples can be quite accurate when studying technology use in the broader American population [3]. All data was stored on encrypted drives and only two researchers had access to the raw data.

We then created a list of top domains for online video watching in America. This included online TV *streaming sites* such as Netflix and Hulu, *premium content sites* such as HBO and Showtime; *broadcast networks* such as CBS, NBC, ABC, and Fox; *cable providers* such as Comcast Xfinity, AT&T DirecTV, Verizon Fios, and Spectrum; and *online video platforms* such as YouTube, Vimeo, Vevo, Twitch, and Crackle. From these 22 domains, we captured 286,409 page views to these video sites. Unfortunately, this misses videos embedded in other platforms, such as YouTube videos embedded in Facebook streams, which are not captured in web histories as distinct page views. We also do not address any video views to pornographic content. Yet this is the most comprehensive look at video viewing on the desktop web that we are aware of, and we believe is important as a first step towards understanding cross-site video use on computers.

For each site, we manually explored the URL pattern for that site to determine which types of URLs matched video playback (vs. search, browsing, login or other activities). We also wrote scripts to gather additional metadata for each video, using the YouTube API or accessing IMDB data for

Figure 1: Video views per session on the top four video domains.



Domain	Users	Page Views	Video Views
YouTube	173	246,603	135,372
Netflix	86	14,776	4,321
Vimeo	65	420	235
Hulu	54	17,768	7,326
HBO	26	5,176	1,127
Facebook Watch	22	110	110
Amazon Prime	18	264	6
NBC	15	190	29
CBS	12	200	93
DirecTV	10	195	15
ABC	10	30	8
FOX	7	37	7
XFinity	6	163	20
Twitch	5	10	4
Spectrum	5	39	17
Vevo	2	7	2
Crackle	1	412	402
Showtime	1	9	1
Total:	**174**	**286,409**	**149,095**

Table 1: Overall use of video sites in our dataset.

shows watched on other sites. For each video we collected the duration, genre/category, title, year produced, and description of the show.

All research was approved by our institutional processes for conducting work with human subjects and log data. Participants were clearly informed about our institutional identity, the exact data that was being collected, and our data retention policies.

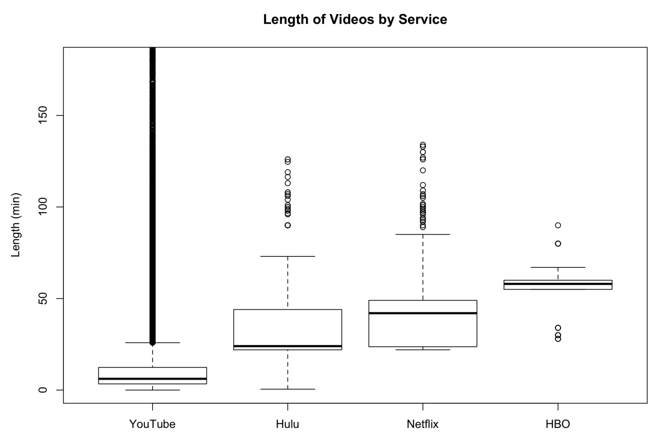
4 FINDINGS

Our dataset contained 9,487,564 total page views from our 174 participants. The 286,299 video page views that we observed made up 3% of all web browsing activity. Using one hour idle session delimiters, there were 43,415 total web browsing sessions in this dataset, 12,894 (30%) including page views to our list of video domains. While video viewing represents a very small percentage of total page views, we find it quite interesting that it occurs in almost one third of web sessions.

Sites Visited

Our participants visited a wide variety of video sites in their datasets. YouTube was by far the most popular with 173 of the 174 users visiting a YouTube page, 246,603 total YouTube pageviews, and 89,581 unique videos played. As shown in Table 1, Netflix, Vimeo, Hulu, HBO, Facebook Watch, and Amazon Prime were visited by the highest number of users overall. The median user visited three unique video domains (of the 20 we analyzed) in their logs, with 25% of users visiting four or more.

Figure 2: Length of videos watched for each of the top video services.



Within a session, 90% of the time our participants only visited one video site. An additional 8% of the time, they only visited two domains, with less than 2% of sessions consisting of visits to more than two video domains. This is quite different from how users browse other types of content, such as news. Previous research has shown that 40% of news sessions contain visits to multiple news domains [5].

Next we were interested in the number of videos that a user watches in a given session, specifically if this varied among sites. Are some sites more “bingeworthy” than others?

The median session that included video watching (hereafter referred to as a "video session") had four video views in it. When looking at specific domains, as shown in Figure 1 for the top four video sites, we can see that certain sites invite watching additional videos within a session. The median session including YouTube videos had four YouTube videos played, compared to sessions with Netflix and Hulu at two videos each, and HBO at only one video per session that included an HBO video. Interestingly, 25% of YouTube sessions had 11 or more videos played, compared to just two for HBO, three for Hulu and four for Netflix. We will return to this data when we explore content length in the next section in addressing the total length of video played on each site.

Content of Videos Watched

We will now move on to explore the content of the videos that our participants watched. Using the YouTube API and data from IMDB for other sources, we captured the category, year produced, and duration of each video. The categories are shown in Figure 5, with Music, Entertainment, People & Blogs, Gaming, and Comedy being the top-watched categories/genres.

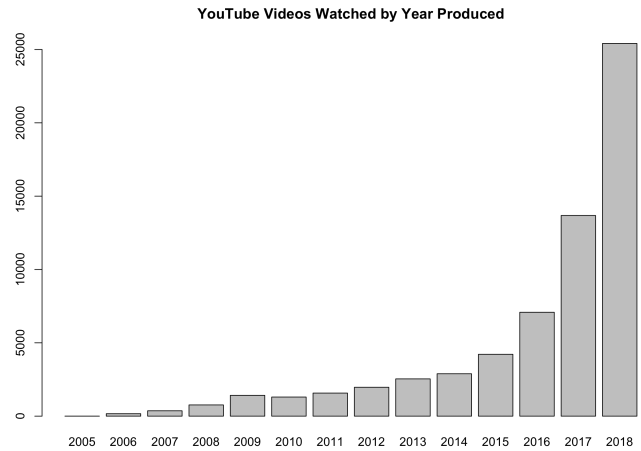
We found it interesting that distinctly user-generated content categories (such as People & Blogs and How To & Style) were vastly more popular than traditional TV and Movie genres (such as Drama, Sports, and Reality). Twelve percent of all videos watched were in the People & Blogs category, compared to only 7% in Comedy, and 2% each in Drama and Sports.

Within a session, users often watched videos from different categories/genres. The median session included videos from two categories, while 25% of sessions had four or more categories included.

Looking further into the length of content watched, Figure 2 shows that the top four video services had quite different lengths of videos viewed. While YouTube videos represented lengths from several seconds to many hours, the middle 50% of videos watched on this service were quite short, ranging from 3.4 to 12.4 minutes long, with a median of 6.2 minutes. Hulu videos were the next longest, with many half-hour network comedy shows represented. The middle 50% of videos on this service ranged from 22 to 44 minutes (the length of 30-minute and 1-hour shows without commercials), with a median of 24 minutes. Netflix included a higher share of longer videos. While the middle 50% was between 24 and 49 minutes, the median length video was 44 minutes long. HBO viewing mostly included one hour dramas, with a few outliers of half-hour comedy shows such as Last Week Tonight and a few longer movies.

When looking deeper into length, we find key differences by category/genre of video. The median length for a video in the Music category was 4.2 minutes. How To & Style videos

Figure 3: YouTube videos watched by year of production.



were twice as long, with a median length of 8.4 minutes. Despite containing both shorter YouTube videos and longer television programs, the Comedy genre had a median length of 4.7 minutes. In contrast, the Drama category, which is only represented in online television sources, had a median length of 55 minutes. Sci-Fi content was even longer, with a median length of 62 minutes.

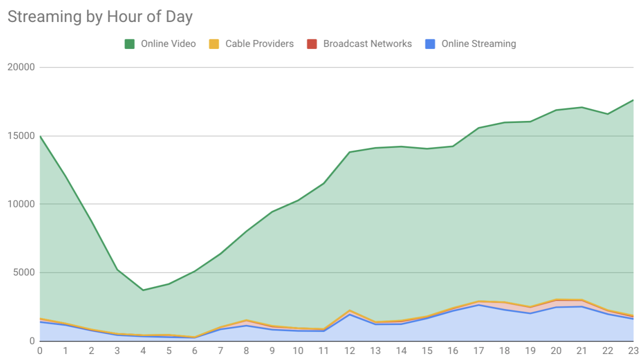
While YouTube represented 91% of all videos watched, we found it interesting that when analyzed by the total duration of videos watched, this decreased to 62% of viewing. Netflix and Hulu jumped from 3% and 5% of videos watched to 14% and 19% of total duration of videos watched. HBO jumped from 1% to 5%. YouTube still comprised the majority of time spent, but with a much smaller dominance when exploring duration.

We next explored differences in the videos our participants watched based on the year when the videos were produced. Only 40% of YouTube videos watched were from 2018, with the majority being from earlier years in a decaying pattern as shown in Figure 3. Yet services such as HBO, which have a large back catalog of shows, had an even smaller fraction of videos (24%) from 2018 that were watched. Users of this service spent time binge watching many seasons of older shows such as The Sopranos, The Wire, and other dramas from the 1990s and early 2000s.

Temporal Patterns of Use

Next, we were interested in the temporal patterns of video watching. Were there particular times of day when users engaged with video content on their computers? Were there differences between types of content? We analyzed the timestamps of all video views in the local timezone of the user.

Figure 4: Video page views by hour of day and type of source.



As shown in Figure 4, overall video viewing on computers hits a low point at 4am and gradually increases all day until hitting a daily high in the 11pm hour. This is similar to what was found by Rigby et al. [18] where the 9-11 pm hours were the most common time to watch. As mentioned above, video views were dominated by YouTube, in the "Online Video" category. Looking at TV content through the other sources, these sites have a small peak in the noon-time hour, and then rise again during the prime-time hours of 5pm-9pm before starting to fall off again. We find it interesting that these professional video sources decline after 9pm, just as YouTube is seeing its daily peak.

Looking into YouTube videos, which were the majority of all videos watched, we can see the topics viewed by hour in Figure 5. It is interesting to note some unique patterns in particular topics. For example, News has a later onset in the day than other types of videos, gaining critical mass after the noontime hour. Sports is also interesting in that it is bi-modal with a peak in the late afternoon before games start, then a trough during the games, and another peak post-game in the 10-11pm hours. During the games, the amount of secondary sports content viewing decreases.

When looking at video length by hour of day, as shown in Figure 6, it is interesting that there are no significant differences in lengths of videos watched at different hours. Our participants did not favor watching significantly longer or shorter videos at any hour of the day. This is different from what users often report [4], where they state in surveys that they prefer shorter videos in the morning and longer videos in the evening. At least on their computers, they are not exhibiting these behaviors.

We next investigated video views by day of week. Were users binging on the weekend but too busy to watch during the week? Figure 7 shows that overall there were no significant differences in video views by day of week. However, if we remove YouTube videos, we do see some differences in playback from other sources. These sources, dominated by Netflix, Hulu, and HBO, tend to be watched less on Mondays and Tuesdays — with Tuesday viewing being 18% lower than Sunday and 25% lower than the highest viewing day on Thursday.

Getting to Video

Finally, we were interested in understanding how users found the online videos that they watched. What were the referring pages to each of the videos viewed? Overall, most videos (78%) were found by browsing on the video platform's website. Five percent of the time, users reached videos via an online search, four percent of the time they came from Reddit, and only two percent of the time they came from social media directly to a video page.

While direct browsing (going to a site first, and then browsing to a video) is the most common way to get to a video, there are some differences between sites, as shown in Figure 8. On Hulu, for example, 97% of all video views came from browsing within the Hulu site, compared to sites of broadcasters, where this was only 69% — links to shows are often tweeted by broadcasters or posted in news articles about specific episodes, driving views from other sources. Web search played different roles on different sites as well, with 5% of YouTube views coming directly from a web search, but only 1% of views on Hulu or Premium Networks such as HBO and Showtime. Netflix and Broadcast Networks yielded 2% of their views directly from clicks in emails, where on all other sites it was 1% or less.

Sessions with videos often involve other types of activities. In the 12,894 sessions with video page views, over 99% also included page views to email, 76% included page views to web search sites, 67% included a set of 3,760 top shopping domains, 56% included social media sites, and 34% included a set of 1,160 top news domains. In all but one video session, other types of content were also loaded, showing that video viewing is not an activity performed in isolation on computers, but is almost always combined with other types of online activities.

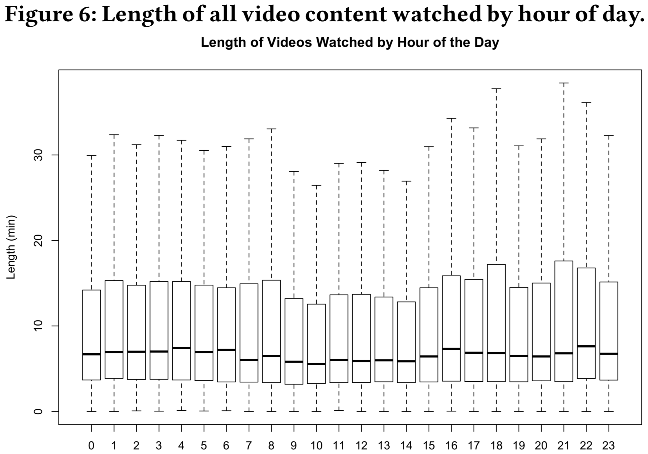
5 LIMITATIONS

While we were able to capture almost 9.5 million page views from our 174 participants, there are several limitations to our study methods that we would like to point out. First, all participants were based in the United States. Given the nature of Amazon Mechanical Turk for recruiting, it is difficult to get representative samples of users outside of the United States. In other countries, different video sites of local networks or cable providers would also be present. Future work should attempt to collect logs from representative samples of users in other countries for comparison.

Figure 5: Categories of videos watched by hour of day.

Category	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	Total
Music	1297	1177	749	422	246	265	267	429	433	588	741	708	883	1034	905	764	613	799	871	895	980	969	1113	1403	17%
Entertainment	971	670	537	291	261	321	347	379	418	553	614	668	817	758	924	865	755	928	1045	1034	1093	1095	1064	1209	16%
People & Blogs	718	579	424	261	209	229	308	302	356	474	517	471	554	655	718	576	634	670	766	748	810	832	767	772	12%
Gaming	526	497	380	249	126	174	240	270	298	397	427	568	538	522	543	602	519	569	724	656	530	592	570	729	11%
Comedy	387	243	356	230	139	122	104	190	162	215	270	259	284	328	304	367	440	500	462	450	459	395	435	427	7%
Howto & Style	470	334	287	129	74	77	109	118	151	175	238	253	236	278	264	353	316	433	344	344	383	429	495	424	6%
News & Politics	300	256	150	145	102	85	106	121	135	170	158	117	187	293	257	317	302	241	314	279	238	313	383	398	5%
Education	279	245	192	98	52	78	77	127	146	158	134	228	176	212	224	241	233	260	267	242	260	311	315	422	5%
Film & Animation	201	161	93	90	44	45	73	74	78	125	158	227	174	251	239	208	231	241	245	285	217	246	249	230	4%
Science & Technology	216	167	159	84	79	82	67	73	82	76	104	172	132	209	212	166	187	233	198	157	203	208	293	256	4%
Animation	108	186	80	14	45	64	32	109	132	65	62	25	62	109	55	59	144	99	69	85	183	209	273	230	2%
Drama	81	43	8	5	13	29	12	78	69	66	73	57	147	102	106	219	102	115	190	254	170	254	158	138	2%
Sports	127	107	59	19	18	29	33	30	30	79	75	125	166	129	169	157	158	118	106	121	90	154	155	215	2%
Travel & Events	91	82	25	19	22	29	12	25	70	74	57	55	55	67	68	82	59	77	69	88	68	85	103	121	1%
Pets & Animals	111	95	71	31	21	15	17	18	75	46	68	48	71	58	49	55	59	92	104	71	91	79	74	82	1%
Autos & Vehicles	44	47	30	4	9	7	12	28	32	31	22	25	40	36	61	42	26	43	67	79	38	65	70	85	1%
Reality	81	165	65	18	0	0	0	0	0	0	0	0	0	40	7	9	8	60	94	62	17	35	70	56	1%
Sci-Fi	16	4	4	6	12	1	4	5	5	5	2	0	8	3	4	0	12	14	98	44	45	54	38	11	0%
Other	26	62	40	17	22	31	37	5	22	28	27	53	33	50	53	50	46	73	38	25	44	56	67	35	1%

Figure 6: Length of all video content watched by hour of day.



Our dataset only comprises an average of 138 days of browsing mostly from the Spring of 2018. The data was collected at the end of June, so some early Summer behaviors are also present in the data. Video viewing might change based on the season and when particular shows are releasing new episodes or when different sports are in-season. Colder and darker winter weather might also affect viewing and is not captured in the timeframe of our data collection.

Also, as mentioned in the Methods section, we could only capture video views that left a distinct page view in the browser logs. Videos embedded in Facebook streams or news articles could not be counted as they did not appear in the logs. Therefore, this analysis can be seen as comprising more deliberate video viewing, where users visited sites whose main purpose is watching online video.

Despite these limitations, we believe that our dataset is the most comprehensive look at cross-site video viewing on computers to date, and a valuable contriution to the literature on interacting with online video.

6 DISCUSSION

By looking at logs of actual video interactions from a diverse sample of the American population, we have been able to find several interesting patterns of usage. This research has enabled us to go beyond previous research that looked at random samples of YouTube videos or focused on survey data of remembered interactions towards analyzing actual behavioral data of interactions with online video. In this section, we will explore the prevalence of short-form video, changing behaviors that we have observed compared to previous studies of video watching, and the lack of many temporal differences in videos watched.

Shorter Videos Remain King

Quite surprising to us was the total dominance of short YouTube videos in our dataset, compared to longer 30- or 60-minute television-style content. 91% of all videos watched were on YouTube, with 75% of these videos being under 12 minutes in length. With so much television watching moving to computers, and the availability of streaming services from networks, cable providers, and OTT providers, we were surprised that there wasn't more of this type of viewing in the dataset.

While shorter content (12 minutes or less) represented 68% of all video starts, it only represented 46% of all viewing time. Long-form content has its place, which is growing over time compared to studies run in 2007 and 2016. However it is still only roughly equal to short-form content in terms of

Figure 7: Video Views by Day of Week.

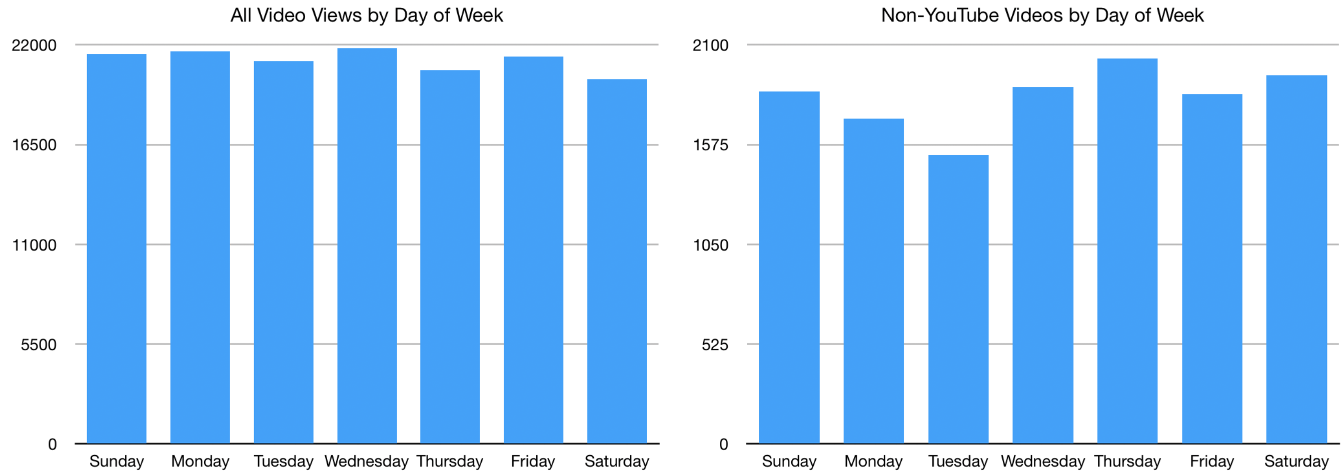
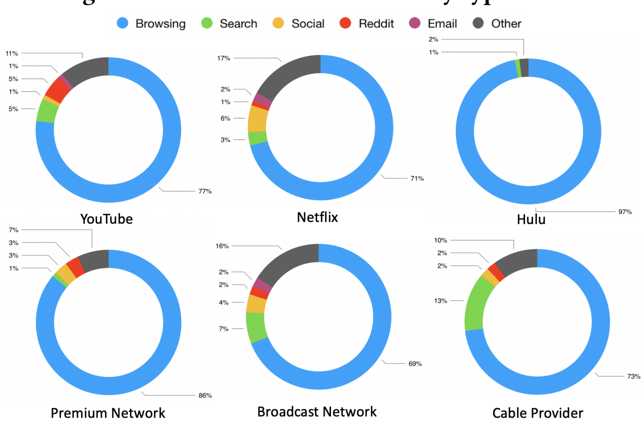


Figure 8: Referrers to video views by type of site.



time spent, and dramatically under-performing in terms of videos played.

Changing Behaviors

We have noticed several larger changes in behaviors in our dataset compared to previous research. Previous studies of YouTube watching have found changing patterns from 2007 [9] to 2013 [8]. We have seen these trends continue, and increase. Music has fallen from 23% to 17% of the total as new YouTube-specific genres, such as How To and Style (6%), and Video Blogs (12%) have emerged. Gaming has continued its increase, from 8.5% in 2013 to 11% in 2018.

The other major trend that we observed was the lengthening of YouTube videos. While 98% were 10 minutes or shorter in 2007 [6] and in 2013 only 2.6% of videos were over 11.7 minutes [8], we found that 25% of the YouTube videos watched in 2018 were over 12 minutes in length.

What is most interesting to us in this data is that even though the average YouTube video has been lengthening, overall behaviors of viewing are still towards shorter productions (i.e. not towards watching 30- or 60- minute shows which made up only 10% of all videos watched across platforms). While most of Hollywood, the major networks, and even new studios such as Netflix, focus on longer form content, the majority of what people are watching on their computers is shorter in duration, a point we will return to in our design implications.

Constant Temporal Preferences

Another area that surprised us in these logs was that user preferences for content do not dramatically change throughout the day. For example, the median length of video watched was constant throughout the day and overall video watching was fairly constant from day to day throughout the week.

In other interviews and surveys that we have conducted as a part of our work, users often state that they have preferences for shorter clips in the morning and longer videos at night, or that they have specific genres of content, such as news, that they prefer at different times of day. However, the data shows otherwise. Despite a few small differences — a slightly later onset in the day for watching News videos, Sports decreasing during games, late-night/early-morning Reality binging — we see few temporal differences in the actual videos that people watch.

7 IMPLICATIONS FOR DESIGN

These findings lead to several implications for the design of new video services and new features of existing video platforms.

Focus on Producing Shorter Videos

In an era where large amounts of longer-form television content is available online through a variety of services from networks, cable providers, and OTT solutions, it was most striking to us that the vast majority (91%) of video viewing was still short-form clips from YouTube. "New" YouTube-specific genres such as how-to videos and video blogs are much more popular than traditional TV and film genres such as drama, sci-fi, or reality shows.

This indicates that there's quite a large market for this shorter-form content on computers, and that professional producers might be able to compete on this shorter-form content, making short how-to programs or other content that reach professional production levels and could gain large audiences on computer platforms, and not just mobile devices which are frequently seen as targets for shorter-form video.

Reduce Focus on Time of Day

Going all the way back to radio transmissions, content has been "programmed" into slots based on time of day. Television production followed this trend, with news in the morning and evening on broadcast networks with "prime-time" shows later in the evening. With the move to online platforms, most producers have followed these same themes, launching online episodes at the time that their broadcast counterparts air.

However, we've seen that there are few temporal differences in how people engage with videos within a genre. Removing this focus on launching shows at particular times, like Netflix has done by moving launches to midnight, gives viewers the chance to watch programs at whatever time they would like, unencumbered by late-evening "broadcast" times.

Likewise, platforms do not have to emphasize specific content types at different times of day. News does not have to be the programming of choice in the morning or noon hours (the data indicates it should actually be the opposite!).

The Importance of Content Browsing Experiences

Unlike online news, where most views come from referrals off-network [5], online video is still dominated by browsing within the walled gardens of specific content sites. The vast majority of the time (78%), videos are found by browsing within the site, and not arrived at through social links or web search. While this varies slightly by service, all sites had over 2/3 of their traffic coming from direct browsing.

Thus, it is important to focus on the experience within a particular site to prioritize content to view, provide well-tuned recommendations, and easily allow for getting to the next episode when binge-watching a show.

It will be interesting if this trend continues, as users have more and more video sites to navigate. Aggregator sites are being built, and are already common on mobile devices, where users can have one place to search for a show and results across all of the services that the user subscribes to will be returned. This is also common on voice-activated remote controls for OTT streaming boxes such as Apple TV. It will be interesting to see if similar solutions come to the web, reducing the role of direct content browsing within particular services over time.

8 CONCLUSION

We have explored the online video watching behaviors of 174 diverse Americans over an average of 138 days of use. By looking across 20 different sites, we analyzed behaviors in overall video watching in terms of categories watched, lengths of videos, and temporal differences in watching behaviors.

This is an important first step in understanding more holistic watching behaviors, instead of just focusing on a particular site such as YouTube or Netflix or relying on survey data of remembered interactions. We hope this will be the start of much more work in this domain, including investigating differences in behaviors in other countries and other more holistic studies of watching on other devices such as tablets or smart TV sets using behavioral data from interaction logs.

REFERENCES

[1] Jeff Baumgartner. 2013. 'Arrested Development' Debut Had 'Noticeable' Impact on Network Traffic. (2013). https://www.multichannel.com/news/arrested-development-debut-had-noticeable-impact-network-traffic-358487

[2] Frank Bentley and Janet Murray. 2016. Understanding Video Rewatching Experiences. In *Proceedings of the ACM International Conference on Interactive Experiences for TV and Online Video (TVX '16)*. ACM, New York, NY, USA, 69–75. https://doi.org/10.1145/2932206.2932213

[3] Frank R. Bentley, Nediyana Daskalova, and Brooke White. 2017. Comparing the Reliability of Amazon Mechanical Turk and Survey Monkey to Traditional Market Research Surveys. In *Proceedings of the 2017 CHI Conference Extended Abstracts on Human Factors in Computing Systems (CHI EA '17)*. ACM, New York, NY, USA, 1092–1099. https://doi.org/10.1145/3027063.3053335

[4] Frank R. Bentley and Danielle Lottridge. 2019. Understanding Mass-Market Mobile Video Behaviors in the Streaming Era. In *Proceedings of the 37th Annual ACM Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA.

[5] Frank R. Bentley, Katie Quehl, Jordan Wirfs-Brock, and Melissa Bica. 2019. Understanding Online News Behaviors. In *Proceedings of the 37th Annual ACM Conference on Human Factors in Computing Systems (CHI '19)*. ACM, New York, NY, USA.

[6] Mathias Bärtl. 2018. YouTube channels, uploads and views: A statistical analysis of the past 10 years. *Convergence*

24, 1 (2018), 16–32. https://doi.org/10.1177/1354856517736979 arXiv:https://doi.org/10.1177/1354856517736979

[7] Juan Pablo Carrascal, Christopher Riederer, Vijay Erramilli, Mauro Cherubini, and Rodrigo de Oliveira. 2013. Your Browsing Behavior for a Big Mac: Economics of Personal Information Online. In *Proceedings of the 22Nd International Conference on World Wide Web (WWW '13)*. ACM, New York, NY, USA, 189–200. https://doi.org/10.1145/2488388.2488406

[8] X. Che, B. Ip, and L. Lin. 2015. A Survey of Current YouTube Video Characteristics. *IEEE MultiMedia* 22, 2 (Apr 2015), 56–63. https://doi.org/10.1109/MMUL.2015.34

[9] Xu Cheng, Jiangchuan Liu, and Cameron Dale. 2013. Understanding the Characteristics of Internet Short Video Sharing: A YouTube-Based Measurement Study. *Trans. Multi.* 15, 5 (Aug. 2013), 1184–1194. https://doi.org/10.1109/TMM.2013.2265531

[10] Robin Murdoch Bikash Mishra Gemma Moorby Bouchra Carlier Gavin Mann, Francesco Venturini. 2015. Digital Video and the Connected Consumer. (2015). https://www.accenture.com/t20150914T152334Z
w__/us-en/_acnmedia/Accenture/Conversion-Assets/DotCom/Documents/Global/PDF/Dualpub_20/Accenture-Digital-Video-Connected-Consumer.pdfla=en#zoom=50

[11] Jan Hess, Benedikt Ley, Corinna Ogonowski, Lin Wan, and Volker Wulf. 2011. Jumping Between Devices and Services: Towards an Integrated Concept for Social Tv. In *Proceedings of the 9th European Conference on Interactive TV and Video (EuroITV '11)*. ACM, New York, NY, USA, 11–20. https://doi.org/10.1145/2000119.2000122

[12] Christian Holz, Frank Bentley, Karen Church, and Mitesh Patel. 2015. "I'm Just on My Phone and They'Re Watching TV": Quantifying Mobile Device Use While Watching Television. In *Proceedings of the ACM International Conference on Interactive Experiences for TV and Online Video (TVX '15)*. ACM, New York, NY, USA, 93–102. https://doi.org/10.1145/2745197.2745210

[13] Jason Kincaid. 2010. YouTube Boosts Maximum Upload Limit to 15 Minutes. (2010). https://techcrunch.com/2010/07/29/youtube-time-limit/

[14] Netflix. 2013. Netflix Declares Binge Watching is the New Normal. (2013). https://media.netflix.com/en/press-releases/netflix-declares-binge-watching-is-the-new-normal-migration-1

[15] Nielsen. 2018. The Nielsen Total Audience Report: Q2 2018. (2018). https://www.nielsen.com/us/en/insights/reports/2018/q2-2018-total-audience-report.html

[16] Matthew Pittman and Kim Sheehan. 2015. Sprinting a media marathon: Uses and gratifications of binge-watching television through Netflix. *First Monday* 20, 10 (2015). https://doi.org/10.5210/fm.v20i10.6138

[17] Jacob M. Rigby, Duncan P. Brumby, Anna L. Cox, and Sandy J.J. Gould. 2018. Old Habits Die Hard: A Diary Study of On-Demand Video Viewing. In *Extended Abstracts of the 2018 CHI Conference on Human Factors in Computing Systems (CHI EA '18)*. ACM, New York, NY, USA, Article LBW016, 6 pages. https://doi.org/10.1145/3170427.3188665

[18] Jacob M. Rigby, Duncan P. Brumby, Anna L. Cox, and Sandy J. J. Gould. 2016. Watching Movies on Netflix: Investigating the Effect of Screen Size on Viewer Immersion. In *Proceedings of the 18th International Conference on Human-Computer Interaction with Mobile Devices and Services Adjunct (MobileHCI '16)*. ACM, New York, NY, USA, 714–721. https://doi.org/10.1145/2957265.2961843

[19] Jacob M. Rigby, Duncan P. Brumby, Sandy J. J. Gould, and Anna L. Cox. 2018. "I Can Watch What I Want": A Diary Study of On-Demand and Cross-Device Viewing. In *Proceedings of the 2018 ACM International Conference on Interactive Experiences for TV and Online Video (TVX '18)*. ACM, New York, NY, USA, 69–80. https://doi.org/10.1145/3210825.3210832

[20] YouTube. 2010. Upload Videos Longer Than 15 Minutes. (2010). https://support.google.com/youtube/answer/71673?co=GENIE.Platform%3DDesktop&hl=en