Analyzing Who and What Appears in a Decade of US Cable TV News

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Figure 1: (a) Our data set contains over 244,000 hours of video aired on CNN, FOX, and MSNBC from January 1, 2010 to July 23, 2019. The screen time of news content (and commercials) in our data set is stable from 2012 onwards, representing near 24/7 coverage. (b) The ratio of time of when female-presenting faces are on screen to when male-presenting faces are on screen is 0.48 to 1 on average, but has risen from 0.41 (to 1) to 0.54 (to 1) over the decade. (c) The top 100 people by face screen time in the data set, with names of the top 10 given. Of the top 100 people, 18 are U.S. politicians and 85 are news presenters (3 are both).

ABSTRACT

Cable TV news reaches millions of U.S. households each day, meaning that decisions about who appears on the news and what stories get covered can profoundly influence public opinion and discourse. We analyze a data set of nearly 24/7 video, audio, and text captions from three U.S. cable TV networks (CNN, FOX, and MSNBC) from January 2010 to July 2019. Using machine learning tools, we detect faces in 244,038 hours of video, label each face’s presented gender, identify prominent public figures, and align text captions to audio. We use these labels to perform screen time and word frequency analyses. For example, we find that overall, much more screen time is given to male-presenting individuals than to female-presenting individuals (2.4x in 2010 and 1.9x in 2019). We present an interactive web-based tool, accessible at https://tvnews.stanford.edu, that allows the general public to perform their own analyses on the full cable TV news data set.

KEYWORDS

Large scale video analysis, cable TV news

1 INTRODUCTION

Cable TV news reaches millions of U.S. households each day, and profoundly influences public opinion and discourse on current events [30]. While cable TV news has been on air for over 40 years, there has been little longitudinal analysis of its visual aspects. As a result, we have little understanding of who appears on cable TV news and what these individuals talk about.

Consider questions like, What is the screen time of men vs. women? Which political candidates and news presenters receive the most screen time? How are victims and perpetrators of violence portrayed? Which foreign countries are discussed the most? Who is on screen when different topics are discussed?

In this paper, we demonstrate that it is possible to answer such questions by analyzing a data set comprised of nearly 24/7 coverage of video, audio, and text captions from three major U.S. cable TV news channels – CNN, FOX (News) and MSNBC – over the last decade (January 1, 2010 to the present). The data set was collected...
by the Internet Archive’s TV News Archive [2]. We focus our analysis (and validation) between January 2010 to July 2019, which includes 244,038 hours (equivalent to about 27.8 years) of footage. Using programmatic and machine learning tools, we label the data set – e.g., we detect faces, label their presented gender, identify prominent public figures, align text captions to audio, and detect commercials. We scope our findings to the news programming portion of the data set (Figure 1a), assuming for 72.1% of the video (175,858 hours) compared to 27.9% for commercials (68,179 hours).

Each of the resulting labels has a temporal extent, and we use these extents to compute the screen time of faces and to identify when individuals are on screen and when words are said. We show that by analyzing the screen time of faces, counting words in captions, and presenting results in the form of time-series plots, we can reveal a variety of insights, patterns, and trends about the data. To this end, we adopt an approach similar to the Google N-gram viewer [42], which demonstrated the usefulness of word frequency analysis of 5.2 million books and print media from 1800 to 2000 to many disciplines, as well as to the GDELT AI Television Explorer [24], which enables analysis of cable TV news captions and on screen objects (but not people). The goal of our work is to enable similar analyses of cable TV news video using labels that aid understanding of who is on screen and what is in the captions.

Our work makes two main contributions.

• We demonstrate that analyzing a decade (January 1, 2010 to July 23, 2019) of cable TV news video generates a variety of insights on a range of socially relevant issues, including gender balance (section 2), visual bias (section 3), topic coverage (section 4), and news presentation (section 5). The details of our data processing, labeling pipeline, and validation for these analyses are described in Supplemental 1.

• We present an interactive, web-based data analysis interface (section 6; available at https://tvnews.stanford.edu), that allows users to easily formulate their own their analysis queries on our annotated data set of cable TV news (section 7). Our analysis interface updates daily with new cable TV news video and allows the general public and journalists to perform their own exploratory analyses on the full the TV news data set. Our data processing code is available as open source.

2 WHO IS IN THE NEWS?

People are an integral part of the news stories that are covered, how they are told, and who tells them. We analyze the screen time and demographics of faces in U.S. cable TV news.

How much time is there at least one face on screen? We detect faces using the MTCNN [66] face detector on frames sampled every three seconds (Supplemental 1.3). Face detections span a wide range of visual contexts ranging from in-studio presenters/guests, people in B-roll footage, or static infographics. Overall, we detect 263M total faces, and at least one face appears on screen 75.3% of the time. Over the decade, the percentage of time with at least one face on screen has risen steadily from 72.9% in 2010 to 81.5% in 2019 and is similar across all three channels (Figure 2).

In the same time period, we also observe an increase in the average number of faces on screen. On CNN and FOX the amount of time when only one face is on screen has declined, while it has remained constant on MSNBC. On all three channels, the amount of time when multiple faces (2 or more) are on screen simultaneously has risen. This accounts for the overall increase in time when at least one face is on screen, though we do not analyze which types of content (with no faces on screen) that this footage is replacing. We note that while the average number of faces has increased in news content, the average number of faces on screen in commercials has remained flat since 2013 (Supplemental 2.1.1).

How does screen time of male-presenting individuals compare to female-presenting individuals? We estimate the presented binary gender of each detected face using a nearest neighbor classifier trained on FaceNet [53] descriptors (Supplemental 1.4). Overall, female-presenting faces are on screen 28.7% of the time, while male-presenting faces are on screen 60.2% of the time, a 0.48 to 1 ratio (Figure 3). These percentages are similar across channels and have slowly increased for both groups (similar to how the percentage of time any face is on screen has increased). The ratio of female- to male-presenting screen time has increased from 0.41 (to 1) to 0.54 (to 1) over the decade (Figure 1b). While the upward trend indicates movement towards gender parity, the rate of change is slow, and these results also reinforce prior observations on the under-representation of women in both film [25] and news media [28].

We acknowledge that our simplification of presented gender to a binary quantity fails to represent transgender or gender-nonconforming individuals [32, 37]. Furthermore, an individual's presented gender may differ from their actual gender identification. Despite these simplifications, we believe that automatically estimating binary presented gender labels is useful to improving understanding of trends in gender representation in cable TV news media.

Which public figures receive the most screen time? We estimate the identity of faces detected in our data set using the Amazon Rekognition Celebrity Recognition API [1]. For individuals who are not currently included (or not accurately detected) by the API, we train our own classifiers using FaceNet [53] descriptors. See Supplemental 1.5 for details.

We identify 1,260 unique individuals who receive at least 10 hours of screen time in our data set. These individuals account for 47% of the 263M faces that we detect in the news content and are on screen for 45% of screen time. The top individual is Donald Trump, who rises to prominence in the 2016 presidential campaigning season and his presidency (Figure 1c). Barack Obama is second, with 0.63× Trump’s screen time, and is prevalent between 2010 (the start of the data set) and 2017 (the end of his second term). Besides U.S. presidents, the list of top individuals is dominated by politicians and news presenters (e.g., anchors, daytime hosts, field reporters, etc.) (Figure 4).

How much screen time do political candidates get before an election? During the 2016 Republican presidential primaries, Donald Trump consistently received more screen time than any other candidate (Figure 5a). In the competitive months of the primary season, from January to May 2016, Trump received 342 hours of screen time, while his closest Republican rival, Ted Cruz, received only 130 hours. In the same timespan, the leading Democratic candidates, Hillary Clinton and Bernie Sanders received more equal screen time.
Figure 2: The percentage of time when at least one face appears on screen has increased on all three channels over the decade (thick lines), with most of the increase occurring between 2015 and 2018. The amount of time when multiple faces are on screen has also increased on all three channels, however the percentage of time with only one face on screen has declined on CNN and FOX, and stagnated on MSNBC.

Figure 3: The percentages of time when male-presenting and female-presenting faces are on screen are similar on all three channels, and have increased over the decade with the rise in all faces noted in Figure 2. Because male- and female-presenting faces can be on screen simultaneously, the lines can add to over 100%.

Figure 4: Distribution of individuals’ screen time, separated by presenters on each channel and non-presenters (stacked). 65% of individuals with 100+ hours of screen time are news presenters. The leading non-presenters are annotated — see Figure 7 for the top news presenters. Note: the three leftmost bars are truncated and the truncated portion includes pre-

(164 hours compared to 139 hours for Clinton); both received far more screen time than the other Democratic primary candidates (Figure 5b). Comparing the two presidential nominees during the period from January 1, 2016 to election day, Trump received 1.9× more screen time than Clinton.

Unlike Trump in 2016, in the run up to the 2012 presidential election, Mitt Romney (the eventual Republican nominee) did not receive as dominating an amount of screen time (Figure 5c). Other Republican candidates such as Herman Cain, Michelle Bachmann, Newt Gingrich, and Rick Santorum have higher peaks than Romney at varying stages of the primary season, and it is not until April 2012 (when his last rival withdraws) that Romney’s screen time decisively overtakes that of his rivals. For reference, Figure 5d shows Barack Obama’s screen time during the same period. As the incumbent president up for re-election, Obama had no significant primary challenger. Obama received more screen time throughout 2011 than Romney because, as the president, he is in the news for events and policy actions related to his duties as president (e.g., U.S. missile strikes in Libya, job growth plan, etc.). In 2012, however, Obama and Romney are comparable. The overall trends are similar when viewed by channel, with Trump dominating screen time in 2016 on all three channels (Supplemental 2.1.3).

Who presents the news? Cable TV news programs feature hosts, anchors and on-air staff (e.g., contributors, meteorologists) to present the news. We manually marked 325 of the public figures who we identified in our data set as news presenters (107 on CNN, 130 on FOX, and 88 on MSNBC). Overall, we find that a news presenter is on screen 28.1% of the time – 27.4% on CNN, 33.5% on FOX, and 23.0% on MSNBC. On CNN, the percentage of time that a news presenter is on screen increases by 13% between 2015 and 2018, while it remains mostly flat over the decade on FOX and MSNBC (Figure 6a).

The news presenters with the most screen time are Anderson Cooper (1,782 hours) on CNN, Bill O’Reilly (1,094 h) on FOX, and Rachel Maddow (1,202 h) on MSNBC. Moreover, while the top presenter on each channel varies a bit over the course of the decade (Figure 7), Cooper and O’Reilly hold the top spot for relatively long stretches on CNN and FOX, respectively. Also, while Maddow appears the most on MSNBC overall, Chris Matthews holds the top spot for the early part of the decade (2010 to 2014). Since 2014, the top presenter on MSNBC has fluctuated on a monthly basis (Figure 7c). The 13% rise in screen time of news presenters on CNN that we saw earlier (in Figure 6a) can largely be attributed to three hosts (Anderson Cooper, Chris Cuomo, and Don Lemon), who see 2.5×, 4.5×, and 5.5× increases in screen time from 2015 onwards (Figure 7a) and account for over a third of news presenter screen time on CNN in 2019.

How does screen time of male- and female-presenting news presenters compare? The list of top news presenters by screen time is dominated by male-presenting individuals. Of the top five news presenters on each channel (accounting for 31%, 22%, and 34% of news presenter screen time on CNN, FOX, and MSNBC, respectively), only one on CNN and FOX; and two on MSNBC are female (Figure 7). Across all three channels, there is a shift towards
Figure 5: Screen time of U.S. presidential candidates during the campaign and primary season of the 2016 and 2012 elections. 
(a) In 2016, Donald Trump received significantly more screen time than the other Republican candidates. (b) Hillary Clinton and Bernie Sanders received nearly equal screen time during the competitive primary season (January–May 2016). (c) In 2012, Mitt Romney did not decisively overtake the other Republican candidates in screen time until he became the presumptive Republican nominee.

Figure 6: (a) The percentage of time when a news presenter is on screen has remained mostly flat on FOX and MSNBC, but has risen by 13% on CNN since 2016. (b–d) Within each channel, the screen time of news presenters by presented-gender (as a percentage of total news presenter screen time) varies across the decade. CNN reaches parity in January–June 2012 and May–August 2015, but has since diverged. Because male- and female-presenting news presenters can be on screen simultaneously, the lines can add to over 100%.

Figure 7: Screen time of the top five presenters on each channel. Since 2016, several of the top presenters on CNN have dramatically risen in screen time. Following Bill O’Reilly’s firing and Megyn Kelly’s departure from FOX in 2017, Sean Hannity and Tucker Carlson have risen in screen time. Since 2013, the variation in screen time among the top five hosts on MSNBC has been low compared to CNN and FOX.

gender parity in the screen time of news presenters early in the decade followed by a divergence (Figure 6b–d).

CNN exhibits gender parity for news presenters in January–June 2012 and May–August 2015 (Figure 6b). However, from September 2015 onward, CNN diverges as the 10% increase in the screen time of male-presenting news presenters (from 14% to 24%) outpaces the 3% increase for female-presenting news presenters (13% to 16%). The increase in male-presenting news presenter screen time on CNN mirrors the increase in overall news presenter screen time on CNN due to an increase in the screen time for Anderson Cooper, Don Lemon, and Chris Cuomo (Figure 7a).

Similarly, the gender disparity of news presenters on FOX decreases from 2010 to 2016 but widens in 2017 due to an increase in the screen time of male-presenting news presenters (Figure 6c). This occurs around the time of (former top hosts) Megyn Kelly’s and Bill O’Reilly’s departure from FOX (6% and 5% of presenter screen time, respectively, on FOX in 2016). Their time is replaced by a rise in Tucker Carlson’s and Sean Hannity’s screen time (3% and 5% of news presenter screen time, respectively, on FOX in 2016 and up to 11% and 7%, respectively, in 2017 and 2018). The increase in female-presenting news presenter screen time in October 2017 occurs when Laura Ingraham’s Ingraham Angle and Shannon Bream’s FOX News @ Night debut.

On MSNBC, the disparity as percentage of news presenter screen time increases from May 2017 to July 2019 (Figure 6d). This is due to a similar drop in the screen time of both male- and female-presenting news presenters. The percentage of time when male-presenting news presenters are on screen falls from 17% to 13%, while the percentage for female-presenting news presenters falls from 14% to 7%. Unlike with CNN and FOX, the change is more distributed across news presenters; the screen time of the top five presenters from 2017 to 2019 is comparatively flat (Figure 7c).

Which news presenters hog the screen time on their shows? We compute the percentage of time a news presenter is on screen
iov of which key topics are discussed, we
count the number of times selected words appear in video captions.

What is the average age of news presenters? We obtain birth-
dates for our list of news presenters from public web sources and
we compute the average age of news presenters on each channel
when they are on screen (Supplemental 1.8). From 2010 to 2019, the
average age of news presenters rises from 48.2 to 51.0 years (Fig-
ure 9). This trend is visible for all three channels, though there are
localized reversals that are often marked by the retirements of older,
prominent hosts; for example, the average news presenter’s age on
CNN falls slightly after Larry King’s retirement in 2010 at age 76.
Across all three channels, female-presenting news presenters are
younger on average than their male-presenting counterparts by 6.3
years. However, the gap has narrowed in recent years.

Are female-presenting news presenters disproportionately
blonde? We manually annotated the hair color (blonde, brown,
black, other) of 145 female-presenting news presenters and
computed the screen time of these groups (Supplemental 1.9). We
find that blondes account for 64.7% of female-presenting news
presenter screen time on FOX (compared to 28.8% for non-blondes).
This gives credence to the stereotype that female-presenting news
presenters on FOX fit a particular aesthetic that includes blonde
hair (advanced, for example, by The Guardian [23]). However,
counter to this stereotype, FOX is not alone; the proportion of
blondes on CNN (56.6% overall and 58.2% since 2015, compared to
38.6% overall for non-blondes) has risen, and, currently, the chance
of seeing a blonde female news presenter is approximately equal
on the two networks (Figure 10). The screen time of blonde female
news presenters is lower on MSNBC (36.6%), where non-blonde
female news presenters account for 55.7%. On MSNBC, brown
is the dominant hair color at 40.8%, but 21.4% is due to a single
brown-haired host (Rachel Maddow). On all three channels, the
percentage of blonde female news presenters far exceeds the
natural rate of blondness in the U.S. (≈ 11% according to the
Bureau of Labor Statistics [10]).

3 HOW ARE INDIVIDUALS PORTRAYED?

Editorial decisions about the images and graphics to include with
stories can subtly influence the way viewers understand a story.
We examine such editorial choices in the context of the Trayvon
Martin shooting.

Which photos of Trayvon Martin and George Zimmerman
appeared most often on each channel? On February 26, 2012,
Trayvon Martin, a 17-year-old high-school student, was fatally
shot by neighborhood watchman George Zimmerman [13]. Media
depictions of both Martin and Zimmerman were scrutinized heavily
as the story captured national interest [45, 56]. We identified
unique photographs of Martin and Zimmerman in our data set
using a K-NN classifier on FaceNet [53] descriptors and tabulated
the screen time of these photos (see Supplemental 1.10).

Figure 11 shows the four photos of Martin (top row) and Zim-
merman (bottom row) that received the most screen time in the
aftermath of the shooting and during Zimmerman’s 2013 trial. In
the initial week of coverage, all three channels used same image
of Martin (purple). This image generated significant discussion about
the “baby-faced” depiction of Martin, although it was dated to a
few months before the shooting. In the ensuing weeks (and later
during Zimmerman’s trial), differences in how the three channels
depict Marin emerge. CNN most commonly used a photograph of
Martin smiling in a blue hat (blue box). In contrast, the most com-
monly shown photo on FOX depicts an unsmiling Martin (orange).
MSNBC most frequently used the black-and-white image of Martin
in a hoodie (pink) that was the symbol for protests in support of
Martin and his family. The three different images reflect significant
differences in editorial decisions made by the three channels.

Depictions of Zimmerman also evolved with coverage of the
shooting and reflect both efforts by channels to use the most up-to
date photos for the story at hand and also the presence of editorial
choices. All three channels initially aired the same image of Zim-
merman (purple). The photo, depicting Zimmerman in an orange
polo shirt, was both out of date and taken from a prior police inci-
dent unrelated to the Martin shooting. A more recent photograph
of Zimmerman (pink) was made available to news outlets in late
March 2012. While CNN and FOX transitioned to using this new
photo, which depicts a smiling Zimmerman, a majority of the time,
MSNBC continued to give more screen time to the original photo.
After mid-April 2012, depictions of Zimmerman on all three chan-
nels primarily show him in courtroom appearances as the legal
process unfolded.

4 WHAT IS DISCUSSED IN THE NEWS?

The amount of coverage that topics receive in the news can influ-
ence viewer perceptions of world events and newsworthy stories.
As a measure of the frequency of which key topics are discussed, we
count the number of times selected words appear in video captions.
Female-presenting
Female-presenting Female-presenting
Male-presenting
Male-presenting
Male-presenting
Larry King... FOX after his inauguration. By contrast, MSNBC continues
6
[0x0]FOX
[0x0]Ed Schultz /f_ired
[6x6]Percent of female news
[12x31]Average age
45
50
55
2010 2013 2016 2019
(a) Blonde female news presenters
(b) Non-blonde female news presenters
0%
25%
50%
75%
100%
Percent of female news presenter screen time
CNN
FOX
MSNBC
2010 2013 2016 2019
(a) Blonde female news presenters (b) Non-blonde female news presenters
0%
25%
50%
75%
100%
Percent of female news presenter screen time
CNN
FOX
MSNBC
2010 2013 2016 2019
Figure 9: The average age of news presenters, weighted by screen time, has increased on all three channels (bold lines). FOX has the highest average age for both male- and female-presenting news presenters.

Figure 10: Blonde female news presenters consistently receive more screen time on FOX than non-blonde female news presenters. CNN catches up to FOX from 2014 onward, while the screen time of blonde female news presenters has risen on MSNBC since 2015. On MSNBC, blonde female news presenters do not receive more screen time than non-blonde female news presenters. Because blonde and non-blonde female news presenters can be on screen at the same time, the lines in (a) and (b) can add to over 100%.

How often are foreign countries mentioned? Foreign country names, defined in Supplemental 1.11, appear in the captions a total of 4,594 times. Most countries receive little coverage (Figure 12), and the eight countries with the highest number of mentions (Russia, Iran, Syria, Iraq, China, North Korea, Israel, and Afghanistan) account for 51% of all country mentions. Russia alone accounts for 11.2%. (If treated as a country, ISIS would rank 2nd after Russia at 8.4%) Of these eight, five have been in a state of armed conflict in the last decade, while the other three have had major diplomatic rifts with the U.S. These data suggest that military conflict and tense U.S. relations beget coverage. No countries from Africa, South America, and Southeast Asia appear in the top eight; the top countries from these regions are Libya/Egypt (11th/12th), Venezuela (32nd), and Vietnam (25th). Bordering the U.S., Mexico is 9th, frequently appearing due to disputes over immigration and trade, while Canada is 21st.

Mentions of individual countries often peak due to important events. Figure 13 annotates such events for the 15 most often mentioned countries. For example, the Libyan Civil War in 2011, the escalation of the Syrian Civil War in 2012-2013, and the rise of ISIS (Syria, Iraq) in 2014 correspond to peaks. The countries below the top 10 are otherwise rarely in the news, but the 2011 tsunami and Fukushima Daiichi nuclear disaster; the 2014 annexation of Crimea by Russia; and the Charlie Hebdo shooting and November Paris attacks (both in 2015), elevated Japan, Ukraine, and France to brief prominence. Since the election of Donald Trump in 2016, however, there has been a marked shift in the top countries, corresponding to topics such as Russian election interference, North Korean disarmament talks, the Iran nuclear deal, and the trade war with China.

For how long do channels cover acts of terrorism, mass shootings, and plane crashes? We enumerated 18 major terrorist attacks (7 in the U.S. and 11 in Europe), 18 mass shootings, and 25 commercial airline crashes in the last decade, and we counted related N-grams such as terror(ism,ist), shoot(ing,er), and plane crash in the weeks following these events (Supplemental 1.12 gives the full lists of terms). Counts for terrorism and shootings return to the pre-event average after about two weeks (Figure 14a-c). Likewise, coverage of plane crashes also declines to pre-crash levels within two weeks (Figure 14d), though there are some notable outliers. Malaysia Airlines Flight 370, which disappeared over the Indian Ocean in 2014, remained in the news for nine weeks, and Malaysia Airlines Flight 17, shot down over Ukraine, also received coverage for four weeks as more details emerged.

Is it illegal or undocumented immigration? “Illegal immigrant” and “undocumented immigrant” are competing terms that describe individuals who are in the U.S. illegally, with the latter term seen as more politically correct [33]. Figure 15 shows the counts of when variants of these terms are used (Supplemental 1.13 gives the full list of variants). Illegal is used on FOX the most (59K times); FOX also has more mentions of immigration overall. From 2012 onward, undocumented has increased in use on CNN and MSNBC, though illegal still appears equally or more often on these channels than undocumented.

How often are honorifics used to refer to President Trump and Obama? Honorifics convey respect for a person or office. We compared the number of times that President (Donald) Trump is used compared to other mentions of Trump’s person (e.g., Donald Trump, just Trump). When computing the number of mentions of just Trump, we exclude references to nouns such as the Trump administration and Melania Trump that also contain the word Trump, but are not referring to Donald Trump (Supplemental 1.14 gives the full list of exclusions).

Our data suggests that although coverage of the incumbent president has increased since the start of Trump’s presidency in 2017, the level of formality when referring to the president has fallen. Trump, in general, is mentioned approximately 3x more than Obama on a monthly basis during the periods of their respective presidencies in our data set. The term President Trump only emerges on all three channels following his inauguration to the office in January 2017 (Figure 16a-c). President is used nearly half of the time on CNN and FOX after his inauguration. By contrast, MSNBC continues
Figure 11: In early coverage of the shooting of Trayvon Martin (by George Zimmerman), all three channels used the same photos of Martin and Zimmerman. However, as the story progressed, depictions of Trayvon (top) differed significantly across channels. Depictions of Zimmerman (bottom) also evolved over time, but largely reflect efforts by channels to use the most up-to-date photo of Zimmerman during criminal proceedings.

Figure 12: Some countries receive more attention in U.S. cable TV news than others. Russia is the largest outlier followed by Iran.

to most commonly refer to him without President. We plot similar charts of President Obama over the course of his presidency from 2010 to January 2017 (Figure 16d-e) and find that, on all three channels, President is used more often than not.

5 WHO IS ON SCREEN WHEN A WORD IS SAID?

People are often associated with specific topics discussed in cable TV news. We analyze the visual association of faces to specific topics by computing how often faces are on screen at the same time that specific words are mentioned. We obtain millisecond-scale time alignments of caption words with the video’s audio track using the Gentle word aligner [47] (Supplemental 1.1).

Which words are most likely to be said when women are on screen? By treating both face detections and words as time intervals, we compute the conditional probability of observing at least one female-presenting (or one male-presenting) face on screen given each word in the caption text (Supplemental 1.15). Because of the gender imbalance in screen time, the conditional probability of a female-presenting face being on screen when any arbitrary word is said is 29.6%, compared to 61.4% for a male-presenting face. We are interested in words where the difference between female and male conditional probabilities deviates from the baseline 31.9% difference.

Figure 17 shows the top 35 words most associated with male- and female-presenting faces on screen. For female-presenting faces, the top words are about women’s health (e.g., breast, pregnant); family (e.g., boyfriend, husband, mom(s), mothers, parenthood, etc.); and female job titles (e.g., actress, congresswoman). Weather-related terms (e.g., temperatures, meteorologist, blizzard, tornadoes) and business news terms (e.g., futures, Nasdaq, stocks, earnings) are also at or near gender parity, and we attribute this to a number of prominent female weatherpersons (Indra Petersons/CNN, Janice Dean/FOX, Maria Molina/FOX) and female business correspondents (Christine Romans/CNN, Alison Kosik/CNN, JJ Ramberg/MSNBC, Stephanie Ruhle/MSNBC, Maria Bartiromo/FOX) across much of the last decade. The top words associated with male-presenting faces on screen are about foreign affairs, terrorism, and conflict (e.g., ISIL, Israelis, Iranians, Saudis, Russians, destroy, treaty); and with fiscal policy (e.g., deficits, trillion, entitlement(s)). The stark difference in the words associated with female-presenting screen time suggests that, over the last decade, the subjects discussed on-air by presenters and guests varied strongly depending on their gender.

Who uses unique words? We define vocabulary to be “unique” to a person if the probability of that individual being on screen conditioned on the word being said (at the same time) is high. Table 1 lists all words for which an individual has a greater than 50% chance of being on screen when the word is said. We limit analysis to words mentioned at least 100 times.) Political opinion show hosts (on FOX and MSNBC) take the most creative liberty in their words, accounting for all but three names in the list.

Which presenters are on screen when the President honorific is said? A news presenter’s use of the President honorific preceding Trump or Obama might set a show’s tone for how these leaders are portrayed. When a presenter is on screen, we find that the honorific term President is used a greater percentage of time for Obama than for Trump, during the periods of their presidencies. On all three channels, most presenters lie below the parity line in Figure 18. However, the average FOX presenter is closer to parity than the average presenter on CNN or MSNBC in uses of President in reference to Trump and Obama (a few FOX presenters lie above the line). Furthermore, Figure 19 shows how the top hosts (by screen time) on each channel are associated with uses of President to refer to Trump over time.
Figure 13: Major peaks in mentions of foreign countries occur around disasters and crises. Since the start of Trump’s presidency, there has been an increase in coverage of Russia, China, and North Korea due to increased tensions and a marked shift in U.S. foreign policy (shaded).

Figure 14: Following a major terrorist attack, mass shooting, or plane crash, usage of related terms increases and remains elevated for 2-3 weeks before returning to pre-event levels. A few plane crashes continued to be covered after this period as new details about the crash (or disappearance in the case of MH370) emerge. In the figure above, lines for individual events are terminated early if another unrelated event of the same category occurs; for example, the San Bernardino shooting (a terrorist attack) in December 2015 occurred three weeks after the November 2015, Paris attacks.

Figure 15: Counts of “illegal immigrant” and “undocumented immigrant” terminology in video captions, by month. Illegal is more common than undocumented on all three channels, but FOX uses it the most. Undocumented only comes into significant use from 2012 onward.

How much was Hillary Clinton’s face associated with the word email? Hillary Clinton’s emails were a frequent news topic in 2015 and during the 2016 presidential election due to investigations of the 2012 Benghazi attack and her controversial use of a private email server while serving as U.S. Secretary of State. During this period, Clinton’s face was often on screen when these controversies were discussed, visually linking her to the controversy. We compute that during the period spanning 2015 to 2016, Clinton’s face is on screen during 11% of mentions of the word email(s) (Figure 20), a significantly higher percentage than the 1.9% of the time that she is on screen overall. This degree of association is similar across all three channels (Supplemental 2.3.1).

6 INTERACTIVE VISUALIZATION TOOL

We have developed an interactive, web-based visualization tool (available at https://tvnews.stanford.edu) that enables the general public to perform analyses of the cable TV news data set (Figure 21).
Figure 17: The distribution of words by difference in conditional probability of a female- versus a male-presenting face being on screen (Supplemental 1.15). The 35 words that are most associated with male- and female-presenting screen time are annotated. Note the stark differences in topic representation in the top male and female associated words: foreign policy, conflict, and fiscal terms (male); and female health, family, weather, and business news terms (female).

Figure 18: Percentage of mentions that use the president honorific for Trump (post-inauguration to January 20, 2017) and Obama (before January 20, 2017) by each news presenter (dots). A majority of presenters on all three channels use president a higher fraction of time when mentioning Obama than they do with Trump. The presenters with the highest screen time on each channel are annotated.

Table 1: Unique words are often euphemisms or insults (urchins □ children, beckster □ Glenn Beck, drugster/rushbo □ Rush Limbaugh, righties □ conservatives, etc.). Others are the names of show segments or slogans. For example, Psychotalk is a segment of the Ed Show; Sean Hannity refers to the liberal media as Obamamania media; and Tucker Carlson brands his own show as the “sworn enemy” of lying, pomposity, smugness, and groupthink. Some rare words become unique due to being replayed often on the news; for example, Kevin McCarthy (U.S. representative) calls Hillary Clinton untrustable and Hillary Clinton uses generalistic in the same sentence as her infamous statement characterizing Trump’s supporters as a “basket of deplorables”.

Although this paper has focused on a static slice of data from January 2010 to July 2019, our public tool ingests new video daily and can be used to investigate coverage of contemporary topics (Figure 22). Our design, inspired by the Google N-gram Viewer [42], generates time-series line charts of the amount of cable TV news video (aggregate time) matching user-specified queries. Queries may consist of one or more filters that select intervals of time when a specific individual appears on screen (name="..."), an on screen face has a specific presented gender (tag="male"), a keyword or phrase appears in the video captions (text="..."), or the videos come from a particular channel (channel="CNN"), program, or time of day.

To construct more complex analyses, the tool supports queries containing conjunctions and disjunctions of filters, which serve to intersect or union the video time intervals matched by individual filters (name="Hillary Clinton" AND text="email" AND channel="FOX"). We implemented a custom in-memory query processing system to execute screen time aggregation queries over the entire cable TV news data set while maintaining interactive response times for the user. In addition to generating time-series plots of video time, the tool enables users to directly view underlying video clips (and their associated captions) that match queries by clicking on the chart.

A major challenge when developing this tool was making an easy-to-use, broadly accessible data analysis interface, while still exposing sufficient functionality to support a wide range of analyses of who and what appears on cable TV news. We call out three design decisions made during tool development.

(1) Limit visualization to time-series plots. Time-series analysis is a powerful way to discover and observe patterns over the decade spanned by the cable TV news data set. While time-series analysis does not encompass the full breadth of analyses presented in this paper, we chose to focus the visualization tool’s design on the creation of time-series plots to encourage and simplify this important form of analysis.

(2) Use screen time as a metric. We constrain all queries, regardless of whether visual filters or caption text filters are used, to generate counts of a single metric: the amount of screen time matching the query. While alternative metrics, such as using word counts to analyze of caption text (section 4) or counts of distinct individuals to understand who appears on a show, may be preferred for certain analyses, we chose screen time because it is well suited to many analyses focused on understanding representation in the news. For example, a count of a face’s screen time directly reflects the chance a viewer will see a face when turning on cable TV news.
Figure 19: Percentage of time when the president honorific is said for Trump while a news presenter is on screen increases after Trump’s inauguration (top 5 presenters for each channel are shown). Chris Cuomo (CNN) drops from over 40% to under 20% in June 2018 with his transition from hosting New Day to Cuomo Primetime. Sean Hannity’s (FOX) decline is more gradual over the course of Trump’s presidency. From 2017 onward, Wolf Blitzer (CNN) is consistently above the other top hosts on any of the three channels (averaging 72%).

Figure 20: Hillary Clinton is on screen up to 33% of the time when email(s) is mentioned (11% on average from 2015 to 2016). This is significantly higher than the percentage of time that Clinton is on screen when any arbitrary word is said (1.9% on average in the same time period).

Also, word counts can be converted into screen time intervals by attributing each instance of a word, regardless of its actual temporal extent, to a fixed interval of time (textwindow=...). As a result, our tool can be used to perform comparisons of word counts as well.

Our decision to make all filters select temporal extents simplified the query system interface. All filters result in a selection of time intervals, allowing all filters to be arbitrarily composed in queries that combine information from face identity labels and captions. A system where some filters yielded word counts and others yields time intervals would complicate the user experience as it introduces the notion of different data types into queries.

(3) Facilitate inspection of source video clips. We found it important for the visualization tool to support user inspection of the source video clips that match a query (Figure 21). Video clip inspection allows a user to observe the context in which a face or word appears in a video. This context in turn is helpful for understanding why a clip was included in a query result, which facilitates deeper understanding of trends being investigated, aids the process of debugging and refining queries, and helps a user assess the accuracy of the automatically generated video labels relied on by a query.

Analysis of user-generated charts

We released the tool on August 19, 2020 and began analyzing user behavior from August 27, 2020 onward. As of September 10, 2020, we have logged 2.6K unique users (based on IP addresses, excluding the authors), who have, on average, created 1.6 new charts containing one or more queries. We provide a FAQ and example queries, and these account for 12% of user-generated charts, while a further 36% are modifications to our examples. Of user-generated charts, 43% plot the screen time of public figures, 3.7% plot screen time by gender, and 59% plot caption text searches (6.7% are multimodal, with both faces and text). Excluding names featured in our examples (e.g., Joe Biden, Donald Trump, Hillary Clinton, Kamala Harris, Elizabeth Warren), the most-queried individuals are Bernie Sanders, Nancy Pelosi, Barack Obama, Mike Pence, along with several other 2020 Democratic presidential candidates. Underlining the value of timely data, users show interest in current events; many common words are related to political polarization (e.g., Qanon, antifa, postal service), COVID-19 (e.g., mask(s)), civil unrest (e.g., George Floyd, protest(s)), looting, the economy (e.g., economy, (un)employment), and technology (e.g., AI, computer science). We hope that allowing the public to analyze such content will improve media understanding.

7 LIMITATIONS AND DISCUSSION

Annotating video using machine learning techniques enables analysis at scale, but it also presents challenges due to the limitations of automated methods. Most importantly, the labels generated by computational models have errors, and understanding the prevalence and nature of labeling errors (including forms of bias [49]) is important to building trust in analysis results. Labeling errors also have the potential to harm individuals that appear in cable TV news, in particular when related to gender or race [9, 16, 26]. As a step toward understanding the accuracy of labels, we validated the output of our face and commercial detection; presented gender estimation; and person identification models (for a small subset of individuals) against human-provided labels on a small collection of frames. The details of this validation process and the measured accuracies of models are provided in the supplemental material.

Despite errors in our computational labeling methods at the individual level, aggregate data about gender representation over time on cable TV news is useful for understanding gender disparities. Many questions about representation in cable TV news media similarly concern the subject of race, but we are unaware of any computational model that can accurately estimate an individual’s race from their appearance (models we have seen have much lower accuracy than models for estimating presented gender). However,
Figure 21: Our interactive visualization tool supports time-series analysis of the cable TV news data set. (Left) Users define queries using a combination of face, caption text, and video metadata filters. The tool generates time-series plots of the total amount of video (aggregate screen time) matching these queries. (Right) To provide more context for the segments of video included in the chart, users can click on the chart to bring up the videos matching the query. We have found that providing direct access to the videos is often essential for debugging queries and better understanding the relevant video clips.

Figure 22: Our tool updates daily with new data and can be used to study contemporary issues. (Left) The amounts of time since December 1, 2019 when the words COVID-19 (and its synonyms) and variants of the root word PROTEST are said on each channel, treating each utterance as a 1s interval. The virus first comes to attention on national cable TV on January 17, 2020 and peaks on March 12. There is a sharp dip in COVID-19 (concurrent with a spike in PROTEST) on May 29, when nationwide, Black Lives Matter protests following George Floyd’s killing took over the headlines. From mid-June onward, COVID-19 coverage rose again; however, the time on FOX is only half that of CNN. (Right) New York governor Andrew Cuomo (blue) rose to prominence in March-May, but has since disappeared from cable TV, while Dr. Anthony S. Fauci (purple) has seen a resurgence in screen time since June.

It may be possible to automatically determine the race of individuals for whom we have an identity label by using external data sources to obtain the individual’s self-reported race. A similar procedure could also be used to obtain the self-identified gender of an individual, reducing our reliance on estimating presented gender from appearance. Such approaches could further improve our understanding of race and gender in cable TV news.

Our system lacks mechanisms for automatically differentiating different types of face appearances. For example, an individual’s face may be on screen because they are included in infographics, directly appearing on the program (as a contributor or guest), or shown in B-roll footage. The ability to differentiate these cases would enable new analyses of how the news covers individuals. Likewise, while our query system can determine when a specific individual’s face is on screen when a word is spoken, it does not perform automatic speaker identification. As a result, the on screen face may not be speaking – e.g., when a news presenter delivers narration over silent B-roll footage. Extending our system to perform automatic speaker identification [20] would allow it to directly support questions about the speaking time of individuals in news programs or about which individuals spoke about what stories.

We believe that adding the ability to identify duplicate clips in the data set would prove to be useful in future analyses. For example, duplicate clips can signal re-airing of programs or replaying of...
popular sound bites. We would also like to connect analyses with additional data sources such as political candidate polling statistics [22] as well as the number and demographics of viewers [46]. Joining in this data would enable analysis of how cable TV news impacts politics and viewers more generally. Finally, we are working with several TV news organizations to deploy private versions of our tool on their internal video archives.

8 RELATED WORK

Prior work in HCI and CSCW has investigated the “information environments” [36] created by technologies such as search engines [34], social media feeds [12], and online news [18]. By determining what information is easily accessible to users, these systems affect people’s beliefs about the world. For example, Kay et al. [36] showed that gender imbalance in image search results can reinforce gendered stereotypes about occupations. Common methods used include algorithmic audits [60], mixed-method studies of online disinfection campaigns [59], and user studies that gauge how algorithms and UI design choices affect user perceptions [21, 58]. While topics such as misinformation spread via social media and online news have become a popular area of research in this space, television remains the dominant news format in the U.S. [4]. Therefore, analysis of traditional media such as cable TV is necessary to characterize the information environments that users navigate.

**Manual analysis of news and media.** There have been many efforts to study trends in media presentation, ranging from analysis of video editing choices [6, 8, 17, 31], coverage of political candidates [38], prevalence of segment formats (e.g. interviews [14]), and representation by race and gender [7, 28, 52, 61]. These efforts rely on manual annotation of media, which limits analysis to small amounts of video (e.g., a few 100s of hours/soundbites [8, 31], five Sunday morning news shows in 2015 [52]) or even to anecdotal observations of a single journalist [15, 45]. The high cost of manual annotation makes studies at scale rare. The BBC 50:50 Project [7], which audits gender representation in news media, depends on self-reporting from newsrooms worldwide. GMPMP [28] relies on a global network of hundreds of volunteers to compile a report on gender representation every five years. While automated techniques cannot generate the same variety of labels as human annotators (GMPMP requires a volunteer to fill out a three-page form for stories they annotate [28]), annotation at scale using computational techniques stands to complement these manual efforts.

**Automated analysis of media.** Our work was heavily inspired by the Google N-gram viewer [42] and Google Trends [29], which demonstrate that automated computational analysis of word frequency, when performed at scale (on centuries of digitized books or the world’s Internet search queries), can serve as a valuable tool for studying trends in culture. These projects allow the general public to conduct analyses by creating simple time series visualizations of word frequencies. We view our work as bringing these ideas to cable TV news video.

Our system is similar to the GDELT AI Television Explorer [24], which provides a web-based query interface for caption text and on screen chyron text in the Internet Archive’s cable TV news data set and recently added support for queries for objects appearing on screen. Our work analyzes nearly the same corpus of source video, but, unlike GDELT, we label the video with information about the faces on screen. We believe that information about who is on screen is particularly important in many analyses of cable TV news media, such as those in this paper.

There is growing interest in using automated computational analysis of text, images, and videos to facilitate understanding of trends in media and the world. This includes mining print news and social media to predict civil unrest [44, 51] and forced population migration [57]; using facial recognition on TV video streams to build connectivity graphs between politicians [50]; using gender classification to quantify the lack of female representation in Hollywood films [25]; understanding presentation style and motion in “TED talk” videos [62, 64]; identifying trends in fashion [27, 40] from internet images; and highlighting visual attributes of cities [5, 19]. These prior works address socially meaningful questions in other domains but put forward techniques that may also be of interest in our cable TV data set.

Finally, time series visualizations of word and document frequencies are commonly used to show changes in patterns of cultural production [48]. We draw inspiration from advocates of “distant reading,” who make use of these visual representations to allow for insights that are impossible from manual inspection of document collections [43].

**Alternative approaches for video analysis queries.** A wide variety of systems exist for interactive video analysis, and existing work in interaction design has presented other potential approaches to formulating queries over video data sets. Video Lens [39] demonstrates interactive filtering using brushing and linking to filter complex spatio-temporal events in baseball video. The query-by-example approach [67] has been used in image [3, 11, 63, 65], and sports domains [54, 55]. These example-based techniques are less applicable for our visualization tool, which focuses on letting users analyze who and what is in cable TV news; typing a person’s name or the keywords in the caption is often easier for users than specifying these attributes by example. Other works from Höferlin, et al. [35] and Meghdadi, et al. [41] propose interactive methods to cluster and visualize object trajectories to identify rare events of interest in surveillance video. Analyzing motion-based events (e.g., hand gestures) in TV news is an area of future work.

9 CONCLUSION

We have conducted a quantitative analysis of nearly a decade of U.S. cable TV news video. Our results demonstrate that automatically-generated video annotations, such as annotations for when faces are on screen and when words appear in captions, can facilitate analyses at scale that provide unique insight into trends in who and what appears in cable TV news. To make analysis of our data set accessible to the general public, we have created an interactive screen time visualization tool that allows users to describe video selection queries and generate time-series plots of screen time. We hope that by making this tool publicly available, we will encourage further analysis and research into the presentation of this important form of news media.
S1 THE DATA SET AND PROCESSING

Our static data set consists of 244,038 hours of video, audio, and captions recorded by the Internet Archive’s TV News Archive [2] from January 1, 2010 to July 23, 2019. It is segmented into 215,771 videos, organized by the date/time of airing and the name of the show. The data set requires 114 terabytes to store, encoded in standard definition (640×360 to 858×480) with the H.264 standard. We use Scanner [10], a distributed video processing framework, to decode the audio track. For example, captions are missing when multiple segments where caption text is either missing or mixed/lower case. The primary causes of failure for caption alignment are truncated captions or instances where the captions do not match the audio content (e.g., due to being attributed to the wrong video). The average speaking time for a single word after alignment is 219 ms.

While the captions are generally faithful to the words being spoken, we observe occasional differences between the captions and the audio track. For example, captions are missing when multiple individuals are speaking (interrupting or talking over each other). The spelling in the captions also sometimes does not reflect the standard English spelling of a word; e.g., mail appears as e-mail and ObamaCare appears as Obama Care. When analyzing these topics in the paper, we account for these spelling/segmentation variants.

S1.1 Captions and time alignment

Closed captions are available from the Internet Archive. The captions are all upper case for the majority of news programming and contain 2.49 billion text tokens, of which 1.94 million are unique (average token length is 3.82 characters). Not all tokens are words (they include punctuation, numbers, misspellings, etc.), however. By a random sample of the set of unique tokens, we estimate that there are 141K unique English words in the data set (± 31K at 95% confidence).

We use the Gentle word aligner [9] to perform sub-second alignment of words in a video’s captions to the video’s audio track, assigning each token a starting and ending time. (The source captions are only coarsely aligned to the video.) Alignment is considered successful if alignments are found for 80% of the words in the captions. By this metric, we are able to align captions for 92.4% of the videos. The primary causes of failure for caption alignment are truncated captions or instances where the captions do not match the audio content (e.g., due to being attributed to the wrong video). The average speaking time for a single word after alignment is 219 ms.

While the captions are generally faithful to the words being spoken, we observe occasional differences between the captions and the audio track. For example, captions are missing when multiple individuals are speaking (interrupting or talking over each other). The spelling in the captions also sometimes does not reflect the standard English spelling of a word; e.g., mail appears as e-mail and ObamaCare appears as Obama Care. When analyzing these topics in the paper, we account for these spelling/segmentation variants.

S1.2 Commercial detection

We observe that commercial segments in the data set are often bracketed by black frames, have captions in mixed/lower case (as opposed to all uppercase for news content), or are missing caption text entirely. Commercials also do not contain » delimiters (for speaker changes). Using these features, we developed a heuristic algorithm that scans videos for sequences of black frames (which typically indicate the start and end of commercials) and for video segments where caption text is either missing or mixed/lower case. The algorithm is written using Rekall [6], an API for complex event detection in video, and is shown in Figure 1. To validate our commercial detection algorithm, we hand annotated 225 hours of videos with 61.8 hours of commercials. The overall precision and recall of our detector on this annotated data set are 93.0% and 96.8% respectively.

Note: we are unable to detect commercials in 9.76% of video (2,713 CNN, 4,614 FOX, and 2,469 MSNBC) because the captions from those videos are unavailable due to failed alignment or missing from the Internet Archive [2].

S1.3 Face detection

We use MTCNN [13] to detect faces in a subset of frames uniformly spaced by three seconds in a video. Performing face detection on all frames is cost prohibitive. Three seconds is on the order of 2x the average shot length (≈ 6.2 seconds between camera cuts) that we estimated for news content using a shot detection heuristic that checks for large differences in color histograms between frames. At this sample rate, we detect 306M faces in total, of which 263M lie in non-commercial video frames. For each of the faces detected, we compute a 128-dimensional FaceNet [11] descriptor from the pixels contained within the face’s bounding box. These descriptors are used to compute additional annotations such as binary gender presentation (S1.4) and person identification for our self-trained models (S1.5).
To estimate the accuracy of face detection, we manually counted the actual number of faces and the number of errors (false positives/negatives) made by the MTCNN [13] face detector in 250 randomly sampled frames from each year of the data (Table 1). Overall precision is high (≈0.98). Recall is lower (≈0.74) because the metric includes missed detection of any face, including non-important or difficult to detect faces (e.g., out-of-focus, partially occluded, very small, extreme side-angled faces); a large fraction of recall errors are in frames with crowds (such as a political rally) where background faces are small and often partially occluded. We also report the percentage of frames that contain at least one error (false positive or false negative), which is on average 14% across the entire data set.

S1.4 Gender classification

We trained a binary K-NN classifier using the FaceNet [11] descriptors. For training data, we manually annotated the presented binary gender of 12,669 faces selected at random from the data set. On 6,000 independently sampled validation examples, the classifier has 97.2% agreement with human annotators. Table 2 shows the confusion matrix and class imbalance between male-presenting faces and female-presenting faces.

Imbalances in the error behavior of the K-NN model can influence the results of an analysis (e.g., recall for females, 93.8%, is lower than males, 98.8%). At present, we do not adjust for these imbalances in the paper. One extension to our analyses would be to incorporate these error predictions into the reported findings. For example, we detected 72.5M female-presenting and 178.4M male-presenting faces in all of the news content (28.9% of faces are female). Adjusting based on the error rates in Table 2, we would expect 5.0M females to be mislabeled as males and 2.0M males to be mislabeled as females, resulting in an expected 76.5M female faces and 175.4M male faces. This shifts the percentage of female faces to 30.4%. Similar adjustments to other analyses where data is analyzed across time or slices (e.g., channel, show, video segments when “Obama is on screen”) can be devised, subject to assumptions about the uniformity and independence of model error rates with respect to slices of the data set or the availability of additional validation data to compute fine-grained error estimates. We do not, however, know of closed-form solutions that are consistently applicable to all of our analyses. These extensions are considered future work, and we focus on salient differences in the paper, the accuracy statistics reported here in S1, and on careful spot-checking of the results (e.g., using the interactive tool) when model accuracies are concerned.

In randomly sampling 6,000 faces for validation (4,109 labeled male by human annotators and 1,891 female), we can estimate that female-presenting individuals comprise 31.5% (±1.2% at 95% confidence) of the faces in the data set.

S1.5 Identifying public figures

To identify individuals, we use the Amazon Rekognition Celebrity Recognition API [1]. This API identifies 46.2% of the faces in the data set. To reduce flickering (where a portion of instances of an individual in a video are missed by Amazon), we propagate these face detections to an additional 10.7% of faces using a conservative...
Table 2: Presented gender confusion matrix between K-NN model generated labels and human labels. The estimated precision and recall for the male-presenting and female-presenting classes are 97.2% and 98.8%; and 97.2% and 93.8%, respectively.

| Human labels | Male | Female |
|--------------|------|--------|
| Male         | 4,058 | 51     |
| Female       | 118   | 1,773  |

Table 3: Amazon Rekognition Celebrity Recognition [1] re-models using the FaceNet [11] descriptors. In the latter case, we known to be inaccurate, we train our own person identification Rekognition Celebrity Recognition API [1] or whose labels are similar “doppelgangers” of individuals in the news. See Table 3 for category correspond to people who are in data set (not just visually verified that the individuals (e.g., politicans, news presents, shooting perpetrators/victims) referenced in the paper do not fall under the “doppelganger” category.

| Screen time | # of individuals | Est. % of doppelgangers |
|-------------|------------------|-------------------------|
| 0-10 min    | 129,138           | -                       |
| 10-15 min   | 8,559             | 80%                     |
| 15-30 min   | 10,664            | 76%                     |
| 30-60 min   | 6,352             | 72%                     |
| 1-2 hr      | 3,403             | 84%                     |
| 2-5 hr      | 2,136             | 68%                     |
| 5-10 hr     | 795               | 52%                     |
| 10-20 hr    | 445               | 4%                      |
| 20-50 hr    | 415               | 4%                      |
| 50-100 hr   | 203               | 0%                      |
| 100-200 hr  | 90                | 0%                      |
| 200 hrs or more| 107            | 0%                      |

Table 3: Amazon Rekognition Celebrity Recognition [1] returns facial identity predictions for 162,307 distinct names in our data set. We noticed that the majority of uncommon names (individuals with less than 10 hrs of screen time) predicted by Amazon are “doppelgangers” of the people who are actually in the news content (false positives). These doppelgangers include a large number of foreign musicians, sports players, and actors/actresses. To evaluate the effect of these errors, we randomly sampled 25 individuals (by name) from each screen time range and visually validated whether the individual is present only as a doppelganger to other individuals. Our results suggest that a threshold of 10 hours is needed to eliminate most of the doppelgangers. We manually verified that the individuals (e.g., politicians, news presenters, shooting perpetrators/victims) referenced in the paper do not fall under the “doppelganger” category.

As mentioned in the paper, 1,260 unique individuals receive at least 10 hours of screen time in our data set, accounting in total for 47% of faces in the data set. We validated a stratified sample of these individuals and estimate that 97.3% of the individuals in this category correspond to people who are in data set (not just visually similar “doppelgangers” of individuals in the news). See Table 3 for the full statistics and methodology of the doppelgangers estimation.

For important individuals who are not recognized by the Amazon Rekognition Celebrity Recognition API [1] or whose labels are known to be inaccurate, we train our own person identification models using the FaceNet [11] descriptors. In the latter case, we determined a person’s labels to inaccurate if they were consistently being missed or mis-detected on visual inspection of the videos. To obtain our own labels, we followed two human-in-the-loop labeling methodologies optimized for people who are common (e.g., a President or news presenter who appears for hundreds of hours) and for people who are uncommon (e.g., a shooting victim or less-known public official). The methodologies are described in S1.5.1 and S1.5.2, respectively. We determined which approach to use experimentally: if we could not find enough training examples for the common person approach, we switched to the uncommon person approach. The individuals for which we use our own labels are listed in Table 4.

Table 5 estimates the precision and recall of the labels for the individuals referenced in our paper analyses (e.g., important political figures and candidates). Precision is influenced by many factors, including the presence of individuals of similar appearance being prominent in the news. Because each individual represents only a small portion of overall face screen time, unbiased recall is difficult to compute without finding all instances of an individual. We perform a best effort attempt to estimate recall by manually counting false negatives in randomly sampled frames from videos known to contain the individual (25 videos, 100 frames per video). We note that the number of samples per individual, found in these frames, varies due to the quantity and nature of an individual’s coverage (e.g., appearances in interviews, and the size and quality of their images).

S1.5.1 Methodology for detecting uncommon individuals. To detect uncommon individuals (with less than = 50 hours of screen time or 60,000 face detections), we use Google Image Search [8] to obtain initial images of the person. Next, we use FaceNet [11] to compute descriptors on these examples. We compute the L2 distances from these descriptors to descriptors for all other faces in the data set and display the faces visually by ascending L2 distance. We select instances of the faces that visually match the person, add them to the example set and repeat the process of computing L2 distances and displaying images until it becomes difficult to find additional examples (the top candidates are all images of other people). To make the selection process more time-efficient, we implemented range navigation and selection to label faces between L2 distance ranges at once if all or nearly all of the faces in the range are the correct person. Even so, the primary limitation of this approach is that the labeling time scales linearly with the frequency of the individual in the data set.

S1.5.2 Methodology for detecting common individuals. To detect common individuals, for whom it is impossible to browse all of their detections, we trained a simple logistic classifier on the FaceNet [11] features. We used Google Image Search [8] to find initial examples and augment those by sampling faces from the data set that are similar to the examples in FaceNet descriptor space. For negative examples, we sample faces randomly and manually inspect the random samples that are most likely (based on L2 distance) to be positive examples. (This step is necessary because common individuals such as Donald Trump are likely to appear in the negative samples due to their high frequency in the data set.) We then use these positive and negative examples to train a model. To improve the model, we sampled faces for which the model produces low
Table 4: Individuals for whom we use our own labels. We use our own labels when no labels from Amazon [1] are available, the Amazon labels are known to have low precision or recall, or to be consistent on major comparisons between individuals labeled with our models and with Amazon.

| Politicians       | Notes                                      |
|-------------------|--------------------------------------------|
| Donald Trump      | Low recall from Amazon                     |
| Hillary Clinton   | Used for consistency to Trump              |
| Barrack Obama     | Used for consistency to Trump              |
| Bernie Sanders    | Used for consistency to Trump              |
| Mitt Romney       | Used for consistency to Trump              |
| Dick Durbin       | Not identified by Amazon                   |

| News presenters   | Notes                                      |
|-------------------|--------------------------------------------|
| Ana Cabrera       | Not identified by Amazon                   |
| Brian Shactman    | Not identified by Amazon                   |
| Bryan Illenas     | Not identified by Amazon                   |
| Dave Briggs       | Not identified by Amazon                   |
| David Gura        | Not identified by Amazon                   |
| Dorothy Rabinowitz| Not identified by Amazon                   |
| Doug McKelway     | Not identified by Amazon                   |
| Ed Lavandera      | Not identified by Amazon                   |
| Griff Jenkins     | Not identified by Amazon                   |
| Jason Riley       | Not identified by Amazon                   |
| Jillian Mele      | Not identified by Amazon                   |
| Jim Pinkerton     | Not identified by Amazon                   |
| JJ Ramberg        | Not identified by Amazon                   |
| Lauren Ashburn    | Not identified by Amazon                   |
| Leland Vittert    | Not identified by Amazon                   |
| Louis Burgdorf    | Not identified by Amazon                   |
| Maria Molina      | Not identified by Amazon                   |
| Natalie Allen     | Not identified by Amazon                   |
| Nicole Wallace    | Not identified by Amazon                   |
| Pete Hegseth      | Not identified by Amazon                   |
| Richard Lui       | Not identified by Amazon                   |
| Rick Folbaum      | Not identified by Amazon                   |
| Rick Reichmuth    | Not identified by Amazon                   |
| Rob Schmitt       | Not identified by Amazon                   |
| Toure Neblett     | Not identified by Amazon                   |
| Trace Gallagher   | Not identified by Amazon                   |
| Yasin Vossoughian | Not identified by Amazon                   |

| Miscellaneous     | Notes                                      |
|-------------------|--------------------------------------------|
| George Zimmerman  | Used for consistency to Martin             |
| Trayvon Martin     | Not identified by Amazon                   |

S1.6 Enumerating news presenters

TV news networks refer to their hosts and staff members using a number of terms (e.g., hosts, anchors, correspondents, personalities, journalists); these terms vary by role and by network. We use the term “news presenter” to refer broadly to anchors, hosts, and on-air staff (contributors, meteorologists, etc.) of a news network, and we manually enumerated 325 news presenters from the three networks Table 6. Our list of names consists of the staff listings on the public web pages of CNN, FOX, and MSNBC, accessed in January 2020, and information manually scraped from Wikipedia for the top 150 shows by screen time (accounting for 96% of news content). Because content is shared between different channels at a network, the list for CNN also includes presenters from HLN, owned by CNN. NBC and CNBC presenters are also included in the MSNBC list. We were unable to identify faces for 18 presenters and these individuals are excluded from the 325 presenters listed. These omitted individuals are either not recognized by Amazon Rekognition [1], not in the video data set (e.g., presenters only on HLN or CNBC), or too rare to detect reliably in our data set (e.g., left before January 1, 2010; joined after July 23, 2019; or very specific domain experts).

Most presenters are enumerated at the granularity of a channel; Anderson Cooper (who is a host on CNN) is considered to be a presenter in any CNN video, but would not be considered a presenter on FOX or MSNBC. We do not differentiate between presenter roles, and a presenter’s role may change over the decade as they are promoted or move from show to show. We also do not track the exact length of employment for each presenter on a network; however, the screen time of presenters on a channel becomes negligible (near zero) after they have left the network (due to changing employer, retiring, or being fired). Some presenters in our data set have moved between channels; for example, Ali Velshi left CNN in 2013 and joined MSNBC in 2016. For individuals who were prominent political figures before becoming news presenters, we track presenter status at the show granularity (e.g., Mike Huckabee, Newt Gingrich, and David Axelrod). Table 6 lists all of the news presenters who we identify.

S1.7 Computing “screenhug score” for presenters

“Screenhug score” is defined in the paper as the percentage of time that a news presenter is on screen in the content portion of their own show. We considered shows with at least 100 hours of news content when listing the top 25 news presenters by their screenhug score.

S1.8 Age for news presenters

We successfully obtained birthdates for 98% of news presenters using DBpedia [3] and manual Google and Wikipedia [12] search. For the birthdates queried from DBpedia, we manually verified the results to eliminate common errors such as the wrong birthdate due to the existence of another person of the same name. In a small number of cases (1%), only the birth year was available; for these individuals, we compute their age from January 1 of their birth year.

We calculate the age of news presenters, weighted by screen time, by assigning each face identified as a news presenter with the age (at day granularity) of the individual on the day that the
| Name                                               | Samples | Est. precision | Samples | Est. recall |
|----------------------------------------------------|---------|----------------|---------|-------------|
| **U.S. political figures and candidates**          |         |                |         |             |
| Amy Klobuchar                                       | 100     | 1.00           | 69      | 0.87        |
| Barack Obama †                                      | 100     | 1.00           | 85      | 0.86        |
| Ben Carson                                          | 100     | 0.99           | 132     | 0.85        |
| Bernie Sanders †                                    | 100     | 0.99           | 42      | 0.83        |
| Beto O’Rourke                                       | 100     | 1.00           | 50      | 0.58        |
| Bill Clinton                                        | 100     | 0.89           | 59      | 0.90        |
| Bill De Blasio                                      | 100     | 1.00           | 55      | 0.89        |
| Bobby Jindal                                        | 100     | 0.99           | 133     | 1.00        |
| Carly Fiorina                                       | 100     | 0.92           | 99      | 0.74        |
| Chris Christie                                      | 100     | 0.98           | 118     | 0.87        |
| Dick Durbin †                                       | 100     | 0.96           | 50      | 0.80        |
| Donald Trump †                                      | 100     | 0.91           | 65      | 0.83        |
| Elizabeth Warren                                    | 100     | 0.97           | 42      | 0.81        |
| Gary Johnson                                        | 100     | 0.99           | 124     | 0.84        |
| George W. Bush                                      | 100     | 0.72           | 71      | 0.80        |
| Harry Reid                                          | 100     | 0.97           | 137     | 0.83        |
| Herman Cain                                         | 100     | 1.00           | 100     | 0.90        |
| Hillary Clinton †                                   | 100     | 0.89           | 136     | 0.84        |
| Jeb Bush                                            | 100     | 0.96           | 79      | 0.92        |
| Jim Gilmore                                         | 100     | 0.98           | 157     | 0.94        |
| Jim Webb                                            | 99      | 0.99           | 158     | 0.89        |
| Joe Biden                                           | 100     | 1.00           | 66      | 0.91        |
| John Boehner                                        | 100     | 1.00           | 84      | 0.95        |
| John McCain                                         | 99      | 0.99           | 196     | 0.91        |
| Jon Huntsman Jr.                                    | 100     | 1.00           | 117     | 0.87        |
| Kamala Harris                                       | 99      | 0.97           | 55      | 0.93        |
| Kellyanne Conway                                    | 100     | 1.00           | 151     | 0.72        |
| Kevin McCarthy                                      | 100     | 1.00           | 70      | 0.97        |
| Lincoln Chafee                                      | 100     | 0.88           | 103     | 0.87        |
| Lindsey Graham                                      | 100     | 1.00           | 107     | 0.88        |
| Marco Rubio                                         | 100     | 1.00           | 93      | 0.85        |
| Martin O’Malley                                     | 100     | 0.92           | 129     | 0.86        |
| Michele Bachmann                                    | 100     | 0.91           | 104     | 0.92        |
| Michelle Obama                                      | 100     | 1.00           | 107     | 0.76        |
| Mike Huckabee                                       | 100     | 1.00           | 299     | 0.96        |
| Mitch McConnell                                     | 99      | 1.00           | 81      | 0.83        |
| Mitt Romney †                                       | 100     | 0.98           | 107     | 0.72        |
| Nancy Pelosi                                        | 100     | 1.00           | 37      | 0.87        |
| Newt Gingrich                                       | 100     | 0.98           | 226     | 0.94        |
| Orrin Hatch                                         | 100     | 0.99           | 115     | 0.94        |
| Paul Ryan                                           | 100     | 0.99           | 104     | 0.84        |
| Pete Buttigieg                                       | 100     | 0.99           | 25      | 0.96        |
| Rand Paul                                           | 100     | 1.00           | 140     | 0.94        |
| Rick Santorum                                       | 100     | 1.00           | 168     | 0.92        |
| Rick Perry                                          | 100     | 0.99           | 154     | 0.77        |
| Ron Paul                                            | 100     | 1.00           | 185     | 0.96        |
| Sarah Palin                                         | 100     | 1.00           | 126     | 0.85        |
| Steve Scalise                                       | 100     | 0.97           | 109     | 0.94        |
| Ted Cruz                                            | 100     | 1.00           | 102     | 0.85        |
| Tim Kaine                                           | 100     | 0.99           | 185     | 0.92        |
| Tulsi Gabbard                                       | 100     | 0.97           | 88      | 0.78        |
| **Miscellaneous**                                   |         |                |         |             |
| George Zimmerman †                                  | 100     | 0.98           | 131     | 0.79        |
| Trayvon Martin †                                    | 100     | 0.95           | 48      | 0.63        |

Table 5: Estimated precision is computed on ≈100 randomly sampled faces identified as each individual. Estimated recall is computed on actual instances of each individual’s face found in a random sample of 2,500 faces, from 25 videos, known to contain each individual. († indicates our models.)
The percentage of female-presenters in the news presenter list is 52%, 42%, and 44% on CNN, FOX, and MSNBC, respectively.

### CNN

Ali Velshi (225.9 hours)  
Alison Kosik (104.3)  
Alisyn Camerota (271.1)  
Amanda Davies (3.4)  
Amaro Wárker (9.5)

### FOX

Abby Huntsman (51.3)  
Ainsley Earhardt (211.9)  
Alan Colmes (65.3)  
Alisyn Camerota (141.3)  
Andrea Tantaros (177.5)

### MSNBC

Abby Huntsman (29.0)  
Al Sharpton (286.7)  
Alec Baldwin (2.5)  
Alex Wagner (174.8)  
Alex Witt (261.3)

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Table 6: Compiled list of news presenters and their screen time in hours. Note that the percentage of female-presenters in the news presenter list is 52%, 42%, and 44% on CNN, FOX, and MSNBC, respectively.
video aired. The average age, weighted by screen-time corresponds to the expected age of a news presenter sampled randomly.

Note that our methodology assumes that the video was aired the same day that it was recorded and does not account for old clips or still images (Figure 2).

S1.9 Hair color for news presenters

Two of the authors independently labeled the visible hair color for each male and female news presenter in 25 frames sampled from the data set. There were five possible labels (blond, brown, black, red, white/gray, and bald). For each news presenter, we calculated the majority label according to each rater. The inter-rater agreement for the majority label for female news presenters was 92.4%. In these cases, the majority label was used in the analysis as the hair color label. The two raters reviewed and agreed upon a hair color label for the 11 female news presenters where their majority labels did not match. Figure 3 shows example faces from each hair color group for the female news presenters that we analyzed.

For male presenters, the data was not analyzed because there was much lower inter-rater agreement (75%). One major cause of inter-rater disagreement was confusion over when to apply the bald and white/gray hair labels. There was only one white-haired female presenter in the data set, and no bald female presenters, contributing to lower disagreement.
S1.10 Images/video of Trayvon Martin and George Zimmerman

We use our own identity labels for Trayvon Martin and George Zimmerman because both individuals are rare overall in the data set and they are not reliably identified by Amazon’s Celebrity Recognition API [1].

First, we separate out faces by their source image (before any editing). In the case of George Zimmerman, who is alive, we make a best effort to group faces from the same source event or setting (e.g., court appearances, interview). Note that the same image can be edited differently, have text overlays, and differ in aspects such as tonality and background (see Figure 4 for examples).

For each individual, we use the FaceNet [11] descriptors (described in S1.3) and perform a clustering (in the embedding space) of the faces that we previously identified as the individual. We cluster with a human-in-the-loop, by constructing a 1-NN classifier (i.e., exact nearest neighbor). We select faces which correspond to unique source images, partition the faces, and then visually examine the resulting clusters. Examining the clusters can reveal new source images or misclassified images; the human can create new labels, fix existing labels, and repeat the process. We repeat the process until the clusters are clean (e.g., over 90% precise). We find that using a 1-NN classifier is sufficient and that only a small number of manual labels are needed (fewer than 200) to obtain good precision and recall in the clusters (Table 7). Figure 4 and Figure 5 show examples from the top four clusters for Trayvon Martin and George Zimmerman, respectively.

8

S1.11 Counting foreign country names

To identify the set of most frequently mentioned countries, we constructed a list of country and territory names from [5], which includes all countries and territories with ISO-3166-1 country codes. We manually augment the list with country name aliases; for example, the Holy See and Vatican are aliases of one another and either term is counted as Vatican City. A few countries such as Mexico and Georgia are substrings of U.S. state names, leading to over-counting in the results. To address this issue, we exclude occurrences of Mexico that are preceded by New and we omit Georgia entirely. (Mentions of Georgia in U.S. cable TV news overwhelmingly refer to the U.S. state and not the country.)

S1.12 Counting terrorism, mass shooting, and plane crash N-grams

To measure how long the media continues to cover events after they take place, we counted the number of times words related to terrorism, mass shootings, and plane crashes appear following an event. Table 8 and Table 9 show the events that were included in the analysis. For terrorism, we count instances of terror(ism,ist), attack, shooting, stabbing, and bombing, which refer to the attack itself; for mass shootings, the list is shoot(ing,er) which refers to the shooting or the mass shooter (searching more restrictively for instances of mass shoot(ing,er,ing) yields a similar result, but sometimes mass is omitted in the news coverage); and for plane crashes the list is (air)plane or airliner followed by crash or missing. Because the keywords to measure news coverage are different between each category of event, the raw counts are not directly comparable across categories.
| Date       | Event                              | Victims |
|------------|------------------------------------|---------|
| 4/15/2013  | Boston Marathon bombing            | 286     |
| 12/2/2015  | San Bernardino shooting             | 30      |
| 6/12/2016  | Pulse nightclub shooting            | 103     |
| 9/17/2016  | 2016 New York and New Jersey bombings | 35      |
| 8/12/2017  | Charlottesville car attack          | 29      |
| 10/31/2017 | 2017 New York City truck attack     | 20      |
| 8/3/2019   | El Paso shooting                    | 46      |
| 4/11/2011  | Minsk Metro bombing                 | 219     |
| 7/22/2011  | Norway attacks                      | 396     |
| 7/17/2014  | Malaysia Airlines flight 17 shootdown | 298     |
| 1/7/2015   | January 2015 Île-de-France attacks | 42      |
| 11/13/2015 | November 2015 Paris attacks        | 551     |
| 3/22/2016  | Brussels bombings                   | 375     |
| 7/14/2016  | Nice truck attack                   | 521     |
| 5/22/2017  | Berlin Christmas market attack      | 68      |
| 6/3/2017   | Manchester Arena bombing            | 273     |
| 8/17/2017  | 2017 London Bridge attack           | 59      |
| 2/19/2020  | 2017 Barcelona attacks              | 176     |
| 1/8/2011   | Tucson, Arizona                     | 21      |
| 7/20/2012  | Aurora, Colorado                    | 82      |
| 12/14/2012 | Newtown, Connecticut                | 30      |
| 9/16/2013  | Washington D.C.                     | 21      |
| 5/23/2014  | Isla Vista, California              | 20      |
| 5/17/2015  | Waco, Texas                         | 27      |
| 12/2/2015  | San Bernardino, California          | 38      |
| 6/12/2016  | Orlando, Florida                    | 103     |
| 7/1/2017   | Little Rock, Arkansas               | 28      |
| 10/1/2017  | Las Vegas, Nevada                   | 481     |
| 11/5/2017  | Sutherland Springs, Texas           | 47      |
| 2/14/2018  | Parkland, Florida                   | 34      |
| 6/17/2018  | Trenton, New Jersey                 | 23      |
| 5/18/2018  | Santa Fe, Texas                     | 24      |
| 11/7/2018  | Thousand Oaks, California           | 25      |
| 8/3/2019   | El Paso, Texas                      | 46      |
| 8/4/2019   | Dayton, Ohio                        | 37      |
| 8/31/2019  | MidlandOdessa, Texas                | 33      |

| Date       | Plane crashes                  | Deaths |
|------------|-------------------------------|--------|
| 1/25/2010  | Ethiopian Airlines Flight 409  | 90     |
| 5/12/2010  | Afriqiyah Airways Flight 771   | 103    |
| 5/22/2010  | Air India Express Flight 812   | 158    |
| 7/28/2010  | Airblue Flight 202             | 152    |
| 11/4/2010  | Aero Caribbean Flight 883      | 68     |
| 1/9/2011   | Iran Air Flight 277            | 77     |
| 7/8/2011   | Hewa Bora Airways Flight 952   | 74     |
| 4/20/2012  | Bhjoa Air Flight 213           | 127    |
| 6/3/2012   | Dana Air Flight 992            | 159    |
| 11/17/2013 | Tatarstan Airlines Flight 363  | 50     |
| 3/8/2014   | Malaysia Airlines Flight 370   | 239    |
| 7/17/2014  | Malaysia Airlines Flight 17    | 298    |
| 7/24/2014  | Air Algérie Flight 5017        | 116    |
| 12/28/2014 | Indonesie AirAsia Flight 8501  | 162    |
| 3/24/2015  | Germanwings Flight 9525       | 150    |
| 8/16/2015  | Trigana Air Flight 267         | 54     |
| 3/19/2016  | Flydubai Flight 981            | 62     |
| 5/19/2016  | EgyptAir Flight 804            | 66     |
| 11/28/2016 | LaMia Airlines Flight 2933     | 71     |
| 2/11/2018  | Saratov Airlines Flight 703    | 71     |
| 2/28/2018  | Iran Aseman Airlines Flight 3704 | 66     |
| 3/12/2018  | US-Bangla Airlines Flight 211  | 51     |
| 5/18/2018  | Cubana de Aviación Flight 972  | 112    |
| 10/29/2018 | Lion Air Flight 610            | 189    |
| 3/10/2019  | Ethiopian Airlines Flight 302  | 157    |

Table 8: Major events included in the list of terrorist attacks and mass shootings.

Table 9: Plane crashes included in the analysis. This list includes all of the commercial airline crashes from 2010 to 2019 involving at least 50 fatalities.

S1.13 Counting illegal and undocumented immigration N-grams

We count the number of times that N-grams related to “illegal” and “undocumented” immigration appear in the captions to measure the prevalence of both terms in discussion around immigration. The N-grams used to measure uses of “illegal” are illegal immigrant(s), illegal immigration, illegals, and illegal alien(s). For “undocumented”, the N-grams are undocumented immigrant(s), undocumented immigration, and undocumented alien(s).

S1.14 Counting usage of the president honorific in reference to Trump and Obama

We measure the number of times the “president” honorific is used when addressing each president. This requires classifying occurrences of the word Trump (and also Obama) in captions as having the “president” honorific, not having the honorific (e.g., Donald Trump or just Trump), or not referring to his person (e.g., Trump University).

For Donald Trump, we only count exact matches of President Trump or President Donald Trump as uses of “president”. To count occurrences of without the honorific, we exclude occurrences preceded by president and instances followed by administration,
campaign, university, and care, which are used in compound nouns with Trump. We also exclude occurrences preceded by the (e.g., to filter out other compound nouns of the form the Trump ...); note that this also removes the Trump presidency, which is not referring to his person, but his presidency. Finally, we exclude Donald Trump's immediate family: Melania, Ivanka, Eric, Barron, and [Donald Trump] Jr. These exclusions of nouns related to Trump (but not directed at his person) were selected by visual examination of the top 100 bigrams containing Trump.

The methodology for counting references to Barack Obama is identical, except that the excluded family members are Michelle, Malia, and Sasha.

S1.15 Measuring visual association between words and male/female-presenting screen time

We compute the conditional probabilities of any male- or any female-presenting face being on screen when a word appears in the text.

The majority of the words in the data set (including rare words, but also misspellings) occur very infrequently ~ 95.6% of unique tokens appear fewer than 100 times in the data set. Because there are few face detection events corresponding to these words, their conditional probability has high variance, often taking on extreme values. In order to remove these words and to make the computation practical, we considered only words that appear at least 100 times in the captions.

From the remaining tokens, we filter out NLTK English stop words [4] and restrict our analysis to the most common words in the data set, considering only the top 10% of remaining words (words that occur over 13,462 times).

We then rank the words according to the difference in conditional probability of female-presenting and male-presenting faces given the word appearing in the caption. The top and bottom words in this list are the most strongly associated with the two presented genders. We report the top 35 words for each presented gender, manually filtering out words in these lists that are human names (e.g., Alisyn is associated with female-presenting screen time because Alisyn Camerota is a presenter on CNN) or news program names (which associate to the genders of hosts).

The top female-associated word, futures, is similar to other highly-ranked words in the list (NASDAQ, stocks, but is also part of the name of a female-hosted TV program (Sunday Morning Futures). 14.6% percent of futures mentions are part of the 3-gram sunday morning futures. The word with the 14th-highest conditional probability newsroom is also both a common news-related word and part of a news program name (CNN Newsroom).

S1.16 Computing unique words for individuals

To determine which individuals and words have strong visual/textual associations, we compute the amount of time each individual was on screen while each word is said. This is used to calculate the conditional probability that a person is on screen given the word being said. To filter out rare words, we only consider words with at least 100 occurrences across the decade. The words with conditional probabilities exceeding 50% for any individual are given in Table 1 in the paper.

S1.17 Measuring visual association between news presenters and the president honorific

We extended the president honorific analysis (methodology in S1.14) to when various news presenters are on screen. The N-grams that are counted remain the same as in S1.14. We start with the list of news presenters described in S1.6, but we only show news presenters with at least 100 total references to Trump and 100 total references to Obama to ensure that there is sufficient data for a comparison. This is to account for news presenter who retired before Trump became president or started after Obama stepped down.

S1.18 Measuring visual association between Clinton and the word email

The Hillary Clinton email scandal and subsequent FBI investigation was a highly polarizing issue in the 2016 presidential election. To measure the degree to which Clinton is visually associated with the issue, represented by the word “email”, we counted the number of times “email(s)” was said, and the number of times it was said while Clinton is on screen.

We count occurrences of email(s), email(s), and electronic mail as instances of email being said in the captions. There are 122K utterances of email in the captions between 2015 and 2017, while Hillary Clinton has 738 hours of screen time in the same time period. Clinton’s face is on screen during 14,019 of those utterances.

S1.19 Detecting interviews

Our algorithm for interviews in TV News searches for interviews between a news presenter (the host) and a named guest X. We search for segments where the guest and the host appear together, surrounded by the guest appearing alone or the host appearing alone. Combining these segments captures an alternating pattern where a host appears, guest appears, ... that is indicative of an interview. The pseudocode for this algorithm is shown in Rekall [6] in Figure 7.

We applied this interview detection algorithm on 44 people across our whole data set. These individuals are listed in Table 10.

We exclude Barack Obama, Donald Trump, and Hillary Clinton due to those individuals appearing too often in video clips and still images. Their appearances along with hosts are often misclassified as interviews. For example, Donald Trump may be shown in a still image or giving a speech while the news content cuts back and forth to a host providing commentary (Figure 6). Events such as town-hall gatherings are sometimes also confused as interviews. As the leading candidates and presidents, Trump, Clinton, and Obama appear the most often in these contexts.

We validated our interview detection algorithm by annotating 100 cable TV news videos which contain interviews for three interviewees: Bernie Sanders, Kellyanne Conway, John McCain. Table 11 shows the estimated precision and recall numbers for the three interviewees, as well as the total amount of interview screen time in ground truth for each interviewee.
Table 10: Detected interview time for prominent U.S. political figures. Newt Gingrich and Mike Huckabee are listed separately because they are both hosts (news presenters) and politicians.

| Interviewee         | Hours |
|---------------------|-------|
| John McCain         | 124.4 |
| Bernie Sanders      | 107.8 |
| Rand Paul           | 98.0  |
| Lindsey Graham      | 93.3  |
| Rick Santorum       | 91.9  |
| Marco Rubio         | 87.9  |
| Kellyanne Conway    | 77.7  |
| Sarah Palin         | 72.0  |
| Paul Ryan           | 67.5  |
| John Kasich         | 63.5  |
| Ted Cruz            | 61.5  |
| Chris Christie      | 61.5  |
| Mitt Romney         | 58.9  |
| Ben Carson          | 49.1  |
| Elizabeth Warren    | 35.4  |
| Mitch McConnell     | 34.7  |
| Carly Fiorina       | 33.7  |
| Cory Booker         | 31.3  |
| Kevin McCarthy      | 31.0  |
| Tim Kaine           | 29.4  |
| Chuck Schumer       | 28.9  |
| Nancy Pelosi        | 28.9  |
| Amy Klobuchar       | 28.5  |
| Jeb Bush            | 26.8  |
| Dick Durbin         | 25.8  |
| John Boehner        | 24.6  |
| Joe Biden           | 24.2  |
| Bill Clinton        | 22.0  |
| Bill De Blasio      | 19.6  |
| George W. Bush      | 19.2  |
| Steve Scalise       | 18.2  |
| Bobby Jindal        | 17.3  |
| Orrin Hatch         | 15.1  |
| Martin O’Malley     | 14.6  |
| Kamala Harris       | 12.9  |
| John Cornyn         | 10.3  |
| Tulsi Gabbard       | 9.6   |
| Harry Reid          | 7.6   |
| Pete Buttigieg      | 7.5   |
| Jim Webb            | 6.1   |
| Beto O’Rourke       | 5.3   |
| Lincoln Chafee      | 4.4   |
| Michelle Obama      | 2.3   |
| Jim Gilmore         | 1.6   |
| Newt Gingrich       | 185.3 |
| Mike Huckabee       | 95.8  |

Table 11: Precision and recall numbers for the interview detector across 100 hand-annotated videos as well as the total amount of interview screen time in ground truth for each interviewee.

| Interviewee     | Hours | Precision | Recall  |
|-----------------|-------|-----------|---------|
| Bernie Sanders  | 3.5   | 91.7%     | 97.5%   |
| Kellyanne Conway| 2.2   | 91.8%     | 89.1%   |
| John McCain     | 0.9   | 86.0%     | 99.5%   |

Figure 6: Example frames from a real and incorrectly detected interview. Note that both follow a pattern of a host and guest being on screen, together and alone. The incorrectly detected interview contains videos and graphics of Donald Trump in lieu of his live person. As the presidents and leading candidates, Trump, Clinton, and Obama are discussed at length by hosts in visual contexts that appear similar to interviews.
# Interviews between a host and a named guest
faces = rekall.ingest(database.table("faces"), 3D)

# Select all faces (3s segments) identified as the
# guest and the faces of all hosts
guest_faces = faces.filter(
    face: face.name = guest_name)
host_faces = faces.filter(
    face: face.is_host)

# Coalesce adjacent segments since individuals are
# often on screen for longer than the 3s sample rate
guest_segs = guest_faces.coalesce(
    predicate = time_gap < 30s,
    merge = time_span)
host_segs = host_faces.coalesce(
    predicate = time_gap < 30s,
    merge = time_span)

# Find segments when a host and the guest are on
# screen at the same time
guest_and_host_segs = guest_segs.join(
    host_segs,
    predicate = time_overlaps,
    merge = time_intersection)

guest_alone_segs = host_segs.minus(
    # the host
    guest_and_host_segs)
host_alone_segs = guest_segs.minus(
    guest_and_host_segs)

# Merge segments when the guest is on screen alone
# with the segments when both the host and guest are
# on screen and consider these to be segments of
# an interview
interview_segs = guest_and_host_segs.join(
    guest_alone_segs,
    predicate = before or after,
    merge = time_span)

# Merge the detected interview segments and return
# the ones that exceed a minimum interview duration
interviews = interview_segs.coalesce()
    .filter(interval:
        interval["t2"] - interval["t1"] >= 240s)

Figure 7: Rekall [6] query to retrieve interviews between a host and a named guest (e.g., Bernie Sanders).

S2 ADDITIONAL ANALYSES

S2.1 Who is in the news?

S2.1.1 How much time is there when at least one face is on screen in commercials? Recall from the paper that the percentage of screen time when a face is on screen in news content has risen from by 8.6%, from 72.9% in 2010 to 81.5% in 2019. This same percentage has only risen slightly in commercials in the same timespan (38% to 41%), suggesting that the increase is not solely due to improvements in video quality.

The average number of detected faces visible on screen is 1.38 in news content and 0.49 in commercials, and these figures vary little between channels. There is a rise in the number of detections over the decade, across all three channels, from 1.2 in 2010 to 1.6 in 2019, with much of the increase since 2015 (Figure 10). By contrast, the average number of faces on screen in commercials rises from 0.42 to 0.52, with the much of the increase occurring before 2012.

S2.1.2 What is the average size of faces? The average size of detected faces in news content, as a proportion of the frame height has also risen slightly from 33% to 35% on CNN and 33% to 36% on MSNBC, but has fallen from 33% to 31% on FOX (Figure 11a). Within commercials, the change is less than 1% on CNN and MSNBC, but has fallen from 38% to 34% on FOX (Figure 11b). Note that some videos have black horizontal bars on the top and the bottom due to the video resolution not matching the aspect ratio as an artifact of the recording (16:9 inside 4:3). We excluded these black bars from the frame height calculation.

S2.1.3 Did the screen time given to presidential candidates vary by channel? There is some variation in the screen time given to candidates across channels, but the overall patterns are similar to the aggregate patterns described in the paper (Figure 8).

S2.1.4 Do shows presented by female-presenting news presenters give more screen time to women overall? An individual show’s overall gender balance is skewed by the gender of its host. For example, the show with the greatest female-presenting screen time is Melissa Harris-Perry on MSNBC and the show with the greatest male screen time is Glenn Beck on FOX.

We use the percentage of female-presenting news presenter screen time out of total news presenter screen time to measure the extent to which a show is female- or male-presented. As a measure of the gender balance for female-presenting individuals who are not presenters (non-presenter), we compute the percentage of female-presenting screen time for faces not identified as a news presenter out of the time for all faces that are not identified as a presenter. We measured the linear correlation between these two percentages to evaluate whether shows that lean toward more female-presenting news presenter screen time also have more screen time for female-presenting non-presenters in general. To exclude short-lived shows and special programming, we limited the analysis to shows with at least 100 hours of news content.

We find no correlation on CNN (slope = 0.03, R^2 = 0.02) and FOX (slope = −0.02, R^2 = 0.01), and a weak positive correlation on MSNBC (slope = 0.09, R^2 = 0.19) (Figure 13). This suggests that shows hosted by female-presenting news presenters do not give proportionally more screen time to female-presenting subjects.
Figure 8: Donald Trump received more screen time than any other Republican candidate in the 2016 election season. The difference is most pronounced on MSNBC. Hillary Clinton and Bernie Sanders received similar amounts of screen time during the competitive period of the presidential primary season (January to May, 2016). Compared to CNN and MSNBC, FOX gave less screen time to the Democratic candidates in 2016. In the 2012 election season, Mitt Romney did not dominate screen time of the Republican candidates until much later in the primary season. Michelle Bachmann received a much larger peak on CNN in January 2012 (compared to FOX and MSNBC) before the Iowa caucuses and after she dropped out of the race. Finally, both Barack Obama, the incumbent Democratic president, and Mitt Romney received more screen time on MSNBC than on CNN and FOX.

Figure 9: The percentage of time when faces are on screen has increased for news content, but has remained static in commercials since 2013.

Figure 10: The average number of faces on screen has increased on all three channels.

Figure 11: The average height of faces on screen has remained mostly constant in both news content and commercials, but there is some variation within the decade. The average heights of faces in news content and commercials are similar.

S2.1.5 Which politicians get interviewed? Which presenters do interviews? Interviews are one of the ways that cable TV news channels bring on experts and provide politicians with a platform to express and guests. Our result contrasts with findings by the GMMP [7] that female journalists write disproportionately more articles about female subjects.
Figure 12: The visual association between Hillary Clinton’s face and the word “emails” follows a similar trend on all three channels, far exceeding the baseline association between Clinton being on screen and any arbitrary word being said. From July to October, 2015, Clinton is shown the most on MSNBC (peaking at 40%) when email is said.

Figure 13: There is little correlation between shows that are predominantly presented by female-presenting news presenters and shows with the most screen time for female-presenting faces who are not news presenters.

Figure 14: Interview time of the 44 politicians (interviewees) tested and hosts (interviewers). Note: Bernie Sanders is labeled Democratic due to his affiliation in the 2016 primary.

Figure 15: In interviews, the host appears overwhelmingly on the left or in the middle; interviewees appear in the middle or on the right.

captions oscillates over time, likely due to major events occurring abroad (Figure 16). However, all three channels follow a similar trajectory.

S2.3 Who is on screen when a word is said?

S2.3.1 Did different channels visually associate Hillary Clinton more with the word email than others? Figure 12 shows the percentage of times when email is said and when Hillary Clinton is on screen.
Figure 16: The number of times when foreign country names appear in the news oscillates. The peaks on all three channels are concurrent, but until 2017, the count of foreign country names was higher on CNN than on FOX and MSNBC.

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