Media Portrayals of Minorities Project

# Appendix to the Report on Media Portrayals

## 2018 Newspaper Coverage of African Americans, Asian Americans, Latinos, Jews, and Muslims

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# Methodology

## Collecting our Data

We use LexisNexis, NexisUni, ProQuest, and Factiva databases to identify articles from all sections of *The New York Times, The Washington Post, The Wall Street Journal,* or *USA Today* between January 1, 2014 and December 31, 2018 that contain root words associated with each of our groups. These root words are as follows (with an ! indicating a search for words with any one or more letter following the root):

African Americans: “African American!” OR “African-American!”
Asian Americans: “Asian American!” OR “Asian-American!”
Latinx: Latino! OR Latina! OR Latinx! OR Hispanic!
Jews: Jew OR Jews OR Jewish! OR Jewry OR Judai! OR Jewess!
Muslims: Muslim! OR Islam!

We subsequently eliminated articles unrelated to our topics of interest by dropping those containing only mentions of unrelated words such as “Latinate” or “Islamabad.” We did not search for root words such as “Chinese American” or “Mexican American” that would capture subsets of our groups; we did not include words like “Torah” or “Quran” that invoke but do not name Jews or Muslims; and we excluded “black” because it is present in a large number of articles unrelated to our interests. These choices ensure that all articles in our dataset are directly related to our groups of interest. We retained all articles for our five-year analyses, and created a separate set of articles from 2018 for our one-year analyses.

## Topic Modeling & Features

To identify general themes within our media data, we used latent semantic analysis with non-negative matrix factorization. We ran topic models on the 2018 data for each of our five groups. We iterated between 10-15 topics, and select the number of topics with maximum coherence within that range. The results yield a list of 25 words associated with each topic.

There were a series of topics that recurred across all groups related to five general themes: culture, education, economics, politics, and law and order. Using the results of the topic modeling, we created a list of words associated with each theme. Each article was then assessed for the presence of one or more words related to the theme, and tagged for the thematic feature if a related word was present in the article.

Through our process, we create “features” for each concept. This allows us to identify articles containing one or more of the words associated with each feature. The feature words associated with each general theme are (with an * indicating a search for words with any one or more letter following the root):

- *Culture*: artist*, museum*, exhibition*, galler*, painting*, sculpture*, architecture, opera, musical, film, movie*, art, arts
- *Education*: education*, student*, academi*, professor*, teacher*, school*, standardized test*, college*, universit*, graduat*, alum*, admissio*, affirmative action, teach, taught, teaching
- *Economics*: unemploy*, econom*, job*, wage*, recession, market, employ*, tax, taxes, worker*, trade, trading, labor*
- *Politics*: democrat*, republican*, elect*, governor*, gubernat*, candidate*, senat*, congress*, donald trump*, donald j trump*, president trump*, campaign*, vote*, voting, ballot*, politic*
- *Law and order*: police*, crime*, criminal*, law enforce*, prison*, jail*, arrest*, court, courts, attorney, legal, jury, juries, juror*, verdict*, prosecutor*, convict*, testif*, lawyer*, robber*, rape*, manslaughter*, homici*, assault*, kidnap*, burglar*, theft*, felon*, misdemeanor*, drug possession, unarm*

Below we present the 25 words associated with each topic for the individual groups. We exclude topics that do not capture an identifiable concept. These results provide the foundation for identifying the general themes, and also reveal specific themes associated with each group. Following the list of topics, we provide the features we generated to explore the presence and associations with each specific theme for the group.

## *African Americans*

### Topics

- Topic 2: democrats, democratic, trump, republican, voters, party, republicans, campaign, candidates, election, governor, senate, president, primary, state, political, democrat, candidate, house, vote, race, win, congressional, senator, elections
- Topic 4: unemployment, rate, economy, jobs, growth, economic, labor, wages, workers, data, market, wage, economists, americans, trump, lowest, recession, companies, tax, average, rates, job, low, economist, employers
- Topic 5: police, officers, department, law, justice, court, case, officer, attorney, investigation, enforcement, judge, criminal, charges, crime, cases, prosecutors, officials, shooting, legal, jury, prison, charged, lawyer, statement
- Topic 6: nfl, players, anthem, kaepernick, league, owners, team, football, player, teams, quarterback, season, colin, 49ers, protests, protest, game, stand, eagles, kneeling, sports, games, reid, grievance, national
- Topic 7: residents, city, housing, council, dc, mayor, district, neighborhoods, dollar, community, neighborhood, bowser, development, area, affordable, cities, local, 000, schools, county, homes, officials, units, public, families
- Topic 8: confederate, monuments, slavery, monument, statue, confederacy, statues, civil, war, history, memorial, charlottesville, slaves, slave, historical, lee, enslaved, south, southern, remove, supremacy, removed, jefferson, carolina, memorials
- Topic 9: admissions, students, harvard, applicants, affirmative, schools, school, admission, student, education, colleges, college, universities, asian, plaintiffs, university, class, action, academic, admitted, scores, lawsuit, diversity, elite, blum
- Topic 11: voter, voting, kemp, vote, voters, registration, ballots, georgia, abrams, election, ballot, suppression, elections, state, fraud, rolls, turnout, rights, laws, polling, polls, absentee, law, registered, id

**Group-Specific Features**

- *NFL*: nfl, kaepernick, anthem, football, quarterback*, 49ers, kneel*
- *Housing*: housing, homes, neighborhood*
- *Confederacy*: confedera*, monument*, statue*, memorial*

## *Asian Americans*

**Topics**

- Topic 2: harvard, admissions, applicants, students, affirmative, plaintiffs, lawsuit, court, trial, race, university, action, admission, process, college, universities, case, admitted, discrimination, fair, colleges, racial, blum, filed, supreme
- Topic 3: democrats, voters, republican, democratic, republicans, party, election, candidates, trump, house, congressional, governor, vote, orange, county, campaign, turnout, districts, state, political, races, primary, district, candidate, seat
- Topic 4: schools, blasio, specialized, test, mayor, students, stuyvesant, high, city, elite, school, plan, admissions, admission, exam, carranza, proposal, seats, parents, middle, education, children, chancellor, prep, black
- Topic 7: crazy, rich, asians, film, chu, movie, golding, kwan, rachel, hollywood, constance, wu, singapore, nick, cast, henry, jon, awkwafina, yeoh, actors, romantic, kevin, warner, movies, casting
- Topic 8: census, households, noncitizen, underenumeration, resides, population, demography, citizenship, declines, noncitizens, hospitals, dependency, accurately, aging, frey, younger, older, question, remaking, count, 2020, appealing, whites, explosion, populations
- Topic 9: voter, kemp, voting, georgia, ballots, registration, vote, abrams, election, voters, suppression, ballot, state, gwinnett, absentee, rights, match, rolls, atlanta, law, fraud, elections, register, polling, intimidation
- Topic 11: herpes, infected, genital, sores, oral, prevalence, 49, transmitted, mcquillan, outbreaks, genitals, infections, aged, virus, symptoms, infects, sex, mouth, disease, sexually, 2000, ages, causes, rates, decline
- Topic 12: fraternity, deng, hazing, psi, delta, prosecutors, pi, baruch, manslaughter, pledges, charges, sentencing, hindering, apprehension, guilty, sentenced, backpack, aggravated, death, members, fraternities, rituals, involuntary, voluntary, pledge

**Group-specific features**

- *Culture entertainment*: actor, movie, hollywood, concert, theater
- *Model minority*: prominent, successful, model minority, achievement
- *Affirmative action*: affirmative action
- *Voting*: votee, ballot, election, absentee

## *Latinos*

**Topics**

- Topic 3: voters, democrats, democratic, republican, party, republicans, election, vote, trump, campaign, candidates, governor, state, senate, primary, democrat, political, candidate, elections, house, race, win, congressional, races, polls
- Topic 4: schools, students, test, school, specialized, blasio, education, high, admissions, scores, city, exam, stuyvesant, mayor, middle, carranza, student, chancellor, admission, tests, asian, teachers, math, academic, parents

asian, teachers, math, academic, parents

- Topic 5: austin, manley, packages, package, explosion, bombings, explosions, injured, bombs, police, bomb, bomber, detonated, exploded, killed, investigators, victims, attacks, bombing, march, blast, mason, authorities, suspicious, devices
- Topic 6: rate, unemployment, economy, growth, jobs, economic, wages, workers, labor, rates, income, market, americans, wage, economists, data, employers, report, recession, average, gains, job, higher, economist, low
- Topic 7: moma, farago, museum, exhibition, org, cotter, art, paintings, brancusi, crowns, kubrick, artists, galleries, sculptures, objects, metmuseum, artist, henson, architecture, malevich, corse, modern, gallery, painting, installation
- Topic 8: police, officers, marijuana, arrests, department, criminal, arrested, enforcement, prosecutors, charges, crime, arrest, justice, law, attorney, court, cases, city, officer, blasio, case, crimes, officials, smoking, public
- Topic 10: harvard, admissions, applicants, affirmative, plaintiffs, students, lawsuit, court, trial, universities, admission, race, action, racial, admitted, colleges, university, blum, discrimination, case, asian, alumni, preferences, supreme, college
- Topic 12: immigration, border, trump, immigrants, undocumented, dreamers, daca, administration, citizenship, security, deportation, wall, house, children, legal, government, policy, illegally, democrats, parliamentx, united, republicans, immigrant, lawmakers, illegal

**Group-specific features**

- *Immigration*: immigra*, migra*, refugee*, asylum*
- *Immigration broad*: immigra*, migra*, refugee*, asylum*, daca, deferred action for childhood arrivals, dreamer*, family separation*, family-separation*, caravan*, border*, border wall*
- *Candidate AOC*: alexandria ocasio-cortez*, alexandria ocasio cortez*
- *All candidates*: alexandria ocasio-cortez*, alexandria ocasio cortez*, antonio delgado*, jesus garcia*, veronica escobar*, sylvia garcia*, michelle lujan grisham*, gil cisneros*, xochitl torres small*, ileana ros-lehtinen*, ileana ros lehtinen*, carlos curbelo*, debbie murcasel-powell*, debbie murcasel powell*, mike levin*, anthony gonzalez*, catherine cortez masto*

## *Jews*

### Topics

- Topic 1: life, family, book, work, way, story, city, school, children, day, know, young, home, man, love, father, told, good, dollar, books, history, women, wrote, mother, died
- Topic 2: farago, org, moma, exhibition, museum, art, metmuseum, paintings, cotter, galleries, henson, objects, metropolitan, artist, smith, artists, crowns, installation, modern, kubrick, photographs, crests, whitney, sculpture, survey
- Topic 3: notice, paid, deaths, condolences, mourns, kapito, schoenfeld, extend, death, passing, beloved, ceo, goldstein, board, jeffrey, heartfelt, chair, family, eric, grandchildren, entire, loving, robert, wife, community
- Topic 4: israel, palestinian, israeli, palestinians, jerusalem, gaza, netanyahu, israelis, peace, hamas, bank, embassy, minister, prime, arab, west, abbas, aviv, tel, state, security, east, capital, fence, benjamin
- Topic 6: trump, president, campaign, party, political, republican, democratic, democrats,

government, state, election, voters, white, support, law, republicans, country, administra tion, leaders, parliamentx, politics, states, group, vote, conservative
- Topic 7: groom, bride, graduated, couple, father, degree, cum, laude, married, mother, received, university, met, retired, officiated, son, daughter, ny, rabbi, nj, master, firm, school, weddings, medical
- Topic 8: poland, holocaust, polish, nazi, germany, camps, german, poles, nazis, jews, war, camp, auschwitz, warsaw, ii, concentration, germans, law, death, europe, crimes, government, survivors, remembrance, complicity
- Topic 9: pittsburgh, synagogue, shooting, bowers, tree, saturday, hate, rabbi, 11, massacre, squirrel, congregation, attack, police, jews, gunman, suspect, killed, victims, violence, community, life, hatred, synagogues, mass

**Group-specific features**
- *Israel/Palestine*: israel*, palestin*, gaza, netanyahu, hamas, west bank, jerusalem, tel aviv
- *Embassy*: embassy
- *Anti-Semitism*: anti-semiti*
- *Pittsburgh*: pittsburgh shooting, squirrel hill, synagogue shooting, tree of life, robert bowers
- *Holocaust*: holocaust*, auschwitz*, hitler*, nazi*, neo-nazi*, swastika*
- *Weddings*: wedding*, bride, groom, grooms, bridal, married, marriage
- *Obituary*: obituar*, death notice

## *Muslims*

### Topics
- Topic 1: syria, syrian, iran, turkey, forces, kurdish, military, russia, trump, troops, assad, states, allies, turkish, islamic, iraq, kurds, iranian, war, administration, fighters, russian, erdogan, weapons, officials
- Topic 2: killed, attack, police, attacks, militants, islamic, group, killing, wounded, authorities, forces, area, officials, military, city, security, terrorist, suicide, injured, officers, death, spokesman, dead, soldiers, civilians
- Topic 3: saudi, arabia, khashoggi, prince, crown, mohammed, kingdom, saudis, salman, bin, riyadh, jamal, consulate, yemen, istanbul, arab, qatar, king, disappearance, turkish, royal, journalist, killing, mbs, erdogan
- Topic 4: art, museum, exhibition, org, moma, artists, paintings, farago, artist, cotter, galleries, objects, gallery, brancusi, kubrick, sculptures, crowns, metmuseum, painting, architecture, installation, modern, henson, sculpture, works
- Topic 5: israel, gaza, israeli, hamas, palestinian, palestinians, jerusalem, fence, netanyahu, israelis, strip, border, protests, peace, blockade, egypt, embassy, militant, rockets, benjamin, abbas, protesters, aviv, tel, jewish
- Topic 7: taliban, afghan, afghanistan, kabul, ghani, insurgents, province, peace, pakistan, afghans, suicide, talks, ashraf, forces, officials, troops, attacks, provincial, wounded, war, nangarhar, jalalabad, bomber, ghazni, insurgent
- Topic 8: republican, democrats, voters, election, party, republicans, democratic, candidates, vote, candidate, senate, elections, parliamentx, campaign, trump, race, democrat, governor, political, house, congressional, seats, elected, primary, races
- Topic 9: court, ban, supreme, justice, travel, case, legal, judge, trump, immigration, law, courts, ruling, administration, justices, decision, states, order, department, countries, author-

ity, judges, entry, lawyers, appeals
- Topic 10: myanmar, rohingya, aung, bangladesh, rakhine, kyi, suu, ethnic, cleansing, san, military, kyaw, genocide, soe, nations, oo, human, rights, burma, wa, reuters, journalists, atrocities, buddhist, camps

**Group-specific features**
- *Terrorism*: terroris*, 'islamic state', isis, isil, 'al qaeda', 'al-qaeda', 'suicide bomb*'
- *Conflict*: violen*, fight*, fighting, combat, war, wars, warring, insurgenc*, rebel*, militant*, killing, killed, casualties
- *Saudi Arabia*: 'saudi arabia', 'mohammed bin salman'
- *Israel/Palestine*: israel, israeli*, palestine, palestinian*,'hamas, jerusalem, netanyahu, gaza
- *Myanmar*: myanmar, rohinga
- *Syria*: syria*, turkey, kurds, assad, erdogan
- *Afghanistan*: afghanistan, afghans, taliban, kabul, ashraf

# Lexical Sentiment Analysis

Our lexical sentiment analysis method evaluates every word in each article to see whether it appears in a lexicon (dictionary) of positive or negative words. The overall sentiment of an article is calculated by summing the positive and negative impacts of the words in the text, and scaling by the overall length of the article (so we have a sense of the density of positive and negative words).

No single sentiment analysis dictionary will do a perfect job of capturing all the positive and negative connotations of words in a particular set of texts. Instead, a lexicon's strength can vary depending on the general subject of the texts under analysis, the writing style of the texts, etc. For this reason, we generate eight different measures of sentiment, using eight different, widely used sentiment dictionaries.

In addition, we take into account words that modify a sentiment, including negations ("not," "hardly") and intensifiers ("very," "extremely"). When any one or more of these words directly precede a word in one of our lexica, the sentiment value of the latter is adjusted accordingly.

Next, in order to calibrate our sentiment values such that a 0 is equivalent to neutral sentiment, we have collected a large corpus of about 45,000 newspaper articles—with no restrictions as to subject or length—whose tone can be assumed to be representative of the average tone of newspaper articles in general. For each of our eight sentiment measures, we standardize the sentiments calculated for this representative corpus, so that the mean is 0 and the standard deviation is 1. Not only does this establish a neutral point for our sentiment—it also makes it possible to average our eight sentiment measures without biasing or overweighting the result towards any particular measure. We rescale the resulting measure to once again have a standard deviation of 1.

The same adjustments (individual standardization parameters as well as the final rescaling) can then be applied to any other set of texts, producing a sentiment value that is easily interpretable relative to the average US newspaper article.

# Regression Analysis

We use standard ordinary least squares (OLS) multivariate regressions to estimate how strongly individual "features"—the presence of one or more words from a particular category in a text—are associated with more positive or more negative sentiment.

Our features simply code for the presence (1) or absence (0) of any one or more words from a category in a text. Since they are binary variables, the interpretation of the regression coefficients is relatively straightforward: the presence of a feature is associated with an expected increase in a text's aggregate sentiment by an amount equal to the regression coefficient.

Note that this expected increase is subject to some standard caveats, of which we briefly mention two. First, estimates of the expected impact of a rare feature and a common feature may differ even when in actual articles their effect is similar. Second, some features co-occur regularly. The rate of co-occurrence is not high enough to raise worries about multicollinearity, but it does mean that it is important to think about which estimated effects are likely to reinforce or, conversely, counteract one another.

# Additional Data

Article count by group and publication, 2018

| | Publication | Articles with one or more mention of the group | Articles with three or more mentions of the group |
|---|---|---|---|
| African Americans | New York Times | 4,154 | 639 |
| | Washington Post | 1,712 | 329 |
| | Wall Street Journal | 326 | 37 |
| | USA Today | 307 | 48 |
| Asian Americans | New York Times | 654 | 169 |
| | Washington Post | 122 | 36 |
| | Wall Street Journal | 64 | 29 |
| | USA Today | 23 | 6 |
| Latinos | New York Times | 2,944 | 638 |
| | Washington Post | 927 | 139 |
| | Wall Street Journal | 244 | 46 |
| | USA Today | 137 | 31 |
| Jews | New York Times | 4,385 | 1,276 |
| | Washington Post | 1,093 | 300 |
| | Wall Street Journal | 420 | 143 |
| | USA Today | 82 | 21 |
| Muslims | New York Times | 5,773 | 1,813 |
| | Washington Post | 2,097 | 640 |
| | Wall Street Journal | 1,007 | 313 |
| | USA Today | 155 | 41 |

## Multivariate regression

*Estimated associations between article tone and the five general themes*

| | |
|---|---|
| Culture | .522<br>(.012) |
| Education | .314<br>(.012) |
| Economics | .077<br>(.012) |
| Politics | -.172<br>(.014) |
| Law and order | -.560<br>(.012) |
| Constant | -.213<br>(.015) |
| Adj R-squared | .181 |
| Number of articles | 26,626 |

Note: Each cell gives the estimated coefficients from OLS regressions, with standard errors in parentheses. All coefficients are statistically significant at the $p < .001$ level.

# Citations of Sources

Embedded URLs are accessible through the online version of the appendix at mediaandminorities.org/reports.

Page 1: Latinos and African Americans are the largest of these groups, constituting approximately 16% and 13% of the US population, respectively. Asian Americans are the next most numerous, at roughly 5%. Jews and Muslims make up much smaller proportions of the American population, at approximately 2% and 1%, respectively.
CIA World Factbook, accessed August 19, 2019.

Page 7: In September, a white police officer fatally shot an African American man in his own apartment, sparking protests against racial profiling and police brutality and ultimately resulting in the officer's termination from the Dallas Police Department.
Matthew Haag, Amber Guyger, Dallas Officer Who Killed Botham Jean in His Home, Is Fired, The New York Times, September 24, 2018.

Page 7: Such increased inclusion of African Americans was not only confined to the entertainment industry; in November, more African American women were elected to Congress than ever before.
Ida A. Brudnick and Jennifer E. Manning, African American Members of The United States Congress: 1870-2018, Congressional Research Service, December 28, 2018.

Page 7: The month with the most negative tone across this time period was July 2016, marked by the consecutive deaths of Alton Sterling and Philando Castile.
Two Police Shootings, Two Videos, Two Black Men Dead, CNN, July 7, 2016.

Page 15: Politically, Latino voters were critical in midterm races in Florida, Texas, and Nevada, among other states.
Jen Manuel Krogstad, Antonio Flores and Mark Hugo Lopez, "Key takeaways about Latino voters in the 2018 midterm elections," Pew Research Center, November 9, 2018.

Page 15: As candidates, Latinos made history in congressional elections: Alexandria Ocasio-Cortez became the youngest woman ever elected, and Veronica Escobar and Sylvia Garcia became Texas's first Latina representatives.
Alex Leary and Natalie Andrews, "House Democratic Majority Is Eager to Challenge Trump—And Its Own Party Leadership," The Wall Street Journal, November 7, 2018.

Page 15: New York City mayor Bill de Blasio announced a plan that would incorporate more black and Latino students into the city's specialized high schools on June 2, and on June 26, Alexandria Ocasio-Cortez won the Democratic Party's primary election for New York's 14th congressional district.
Shane Goldmacher and Jonathan Martin, "Alexandria Ocasio-Cortez Defeats Joseph Crowley in Major Democratic House Upset," The New York Times, June 26, 2018.
Bill De Blasio, "Mayor Bill de Blasio: Our specialized schools have a diversity problem.

Let's fix it," Chalkbeat, June 2, 2018.

Page 23: Domestically, Ilhan Omar of Minnesota and Rashida Tlaib of Michigan became the first Muslim women ever elected to the US Congress.
    Michelle Boorstein, Mariaa Iati, Julie Zauzmer, "The Nation's First Two Muslim Congresswomen Are Sworn in, Surrounded by the Women They Inspired," The Washington Post, January 3, 2019.

Page 23: At the same time, anti-Muslim activities and Islamophobia continued to rise, which some attribute to President Trump's inflammatory, xenophobic rhetoric.
    "Anti-Muslim Activities in the United States," New America.

Page 23: Legal debate over the President's controversial 2017 "Muslim ban" on immigration intensified, culminating in a Supreme Court decision to uphold the Executive Order in June.
    "Timeline of the Muslim Ban," ACLU Washington.

Page 23: In the Middle East, Palestinians experienced violence and Israeli settlement expansion while President Trump relocated the US embassy from Tel Aviv to Jerusalem and terminated funding to UNRWA, the main refugee agency for Palestinians.
    Human Rights Watch, "Israel and Palestine: Events of 2018," World Report 2019, March 30, 2019.
    "The Events That Shook the Palestinian Territories in 2018," Al Jazeera, December 30, 2018.

Page 23: Civil conflict continued in Syria, and roughly 12 million (mostly Muslim) civilians remained refugees or internally-displaced.
    "Syria's Civil War Explained from the Beginning," Al Jazeera, April 14, 2018.

Page 23: Further east, the Taliban launched major attacks in Afghanistan in response to an increase in American troop deployment, and security forces continued their extensive ethnic cleansing campaign against the Rohingya in Myanmar.
    "The U.S. War in Afghanistan," Council on Foreign Relations, 2019.
    John Sifton, "Myanmar's 'Genocidal Acts' Demand UN Action," Human Rights Watch, October 26, 2018.

Page 25: This is striking, given that the UN has determined that their situation includes "genocidal acts" and labeled it "a human rights catastrophe" replete with widespread murder, mass rape, disappearances, arson, looting and torture.
    Gabriella Canal, "Rohingya Muslims Are the Most Persecuted Minority in the World: Who Are They?," Global Citizen, February 10, 2017.
    John Sifton, "Myanmar's 'Genocidal Acts' Demand UN Action," Human Rights Watch, October 26, 2018.

Page 26: This is the case even though many public officials view the "Muslim ban"—which barred nationals from six Muslim-majority countries from entering the US for a set period of time—as a reflection of "anti-Muslim sentiment," "institutionalized Islamophobia," and "religious intolerance."

Meg Wagner, Brian Ries, and Veronica Rocha, "Supreme Court Upholds Travel Ban," CNN, June 27, 2018.
Justin Wise, "Amnesty International: Supreme Court upholding Trump travel ban is a 'catastrophe'," The Hill, June 26, 2018.

Page 26: It is sometimes possible to avoid using the words "Muslim" or "Islam"—such as when reporters substitute "Daesh" for "Islamic State"—yet journalists cannot simply stop covering incidents of violence that are significant global news stories.
Laura Reston, "World leaders have taken to calling ISIS "Daesh," a word the Islamic State hates." The New Republic, 2015.

# Additional Sources for our Methods

For additional information on our methods, see https://www.mediaandminorities.org/methods/.

For scholarly publications that use our methods, see: https://www.mediaandminorities.org/publications/.