Sinclair Broadcasting and Racial Resentment: Evidence from Google Trends

April 8, 2021

This paper uses Google search terms containing offensive language as a proxy measure for racial animus. Following the practice of similar works (Stephens-Davidowitz, 2014; Chae, Clouston, Hatzenbuehler, et al., 2015; Chae, Clouston, Martz, et al., 2018; Isoya and Yamada, 2021), I use coded language to refer to these terms. The words themselves can be found in Table **??**

1 Introduction

Can media coverage influence racial resentment? Empirical studies suggest that when white Americans understand welfare policies to threaten their privileged status in the U.S. Social hierarchy, their resentment of minorities increases and their support for welfare decreases (Willer, Feinberg, and Wetts, 2016; Wetts and Willer, 2018). This tendency seems to be weaponed by conservative media institutions and politicians, who seem to encourage racial animus to erode support for social programs, as in the infamous example of the "Welfare Queen" narrative, a racial stereotype employed to undercut support for the Aid to Families with Dependent Children (AFDC). However, the link between traditional media coverage and racial resentment has not been extensively studied.

I propose a study exploiting the expansion of the Sinclair Broadcasting Group from 2004-2021 to understand how conservative media messaging impacts racial resentment in a media market. The expansion of the Sinclair Broadcasting Group during this period provides the basis for a difference-in-differences analysis estimating the effect of Sinclair Media purchasing a station on racial animus in an area. I use the concentration of racially charged Google searches a proxy for the intensity of racial animus in an area. This measure has previously been used to measure the contributions of racial resentment towards African-American mortality (Chae, Clouston, Martz, et al., 2018; Chae, Clouston, Hatzenbuehler, et al., 2015), election outcomes (Stephens-Davidowitz, 2014), and economic inequality (Connor et al., 2019), and does not suffer from the same social censoring issues that confound traditional measures.

2 Theoretical Framework

3 Background

3.1 Sinclair Broadcast Group

During the period of 2004-2021, the Sinclair Broadcasting Group bought or sold stations in 67 media markets. I use this pattern of expansion as the basis for a difference-in-differences analysis.

I extract a record of which markets Sinclair has a presence in from the company's yearly filings with the Securities and Exchange Commission, which report each station owned by the company at the end of the time of filing a map of which regions Sinclair moved into / out of can be seen in figure 4a. This strategy has previously been used by Miho (2018) to track Sinclair Expanison over the period of 1995-2017. SEC filings have an advantage over the typical sets data used to track network expansion maintained by the Nielsen Corporation as they are publicly available, so the findings can be easily reproduced.

3.2 Does Sinclair Have a Racial Bias?

This analysis assumes that Sinclair stations differ from non-Sinclair stations on coverage of racial issues: if Sinclair stations deploy the same coverage on racial issues as other stations, then we would expect to see no difference in levels of racial resentment between Sinclair and non-Sinclair media markets. So, it must be asked: does Sinclair coverage have a racially-conservative bent? Admittedly, there have been no large-scale analyses of the effects of Sinclair ownership on coverage of racial issues. Nonetheless, I submit that there is evidence to show Sinclair Stations cover racial issues in a more conservative light than they would absent Sinclair ownership.

Previous research has demonstrated that Sinclair acquisition of a network is associated with a sharp rightwards shift in its coverage (Martin and McCrain, 2019). I argue this effect extends to its framing of racial issues.

This year, the Sinclair corporation drew ire for a series of "must-run" segments on police violence following the murder of George Floyd pushing the "black-on-black violence" canard and advocating for a military response to the protests (Pleat and Savillo, 2020; Pleat, 2020).

In analyzing the effects of news coverage on racial animus, it might be natural to examine the expansion of Fox News, which occupies a position in the public consciousness as among the most conservative stations on racial issues, and is the most trusted media outlet among Republican and Republican-leaning respondents in many polls (Mark Jurkowitz and Walker, 2020). However, I choose to use Sinclair over Fox News Stations for two reasons. First, Fox News' expansion strategy has involved purchasing a larger stations. As television companies in the US can only expand until they broadcast to 39% of U.S. households (Scherer, 2018), Fox News has been able to buy fewer stations than Sinclair, which entails a smaller sample size of stations that changed ownership. Second, Fox News' expansion primarily happened before 2004, the first year for which Google Trends data is available, which further limits the sample size of stations which changed ownership for which there is data on racial animus.

3.3 Google Trends Data

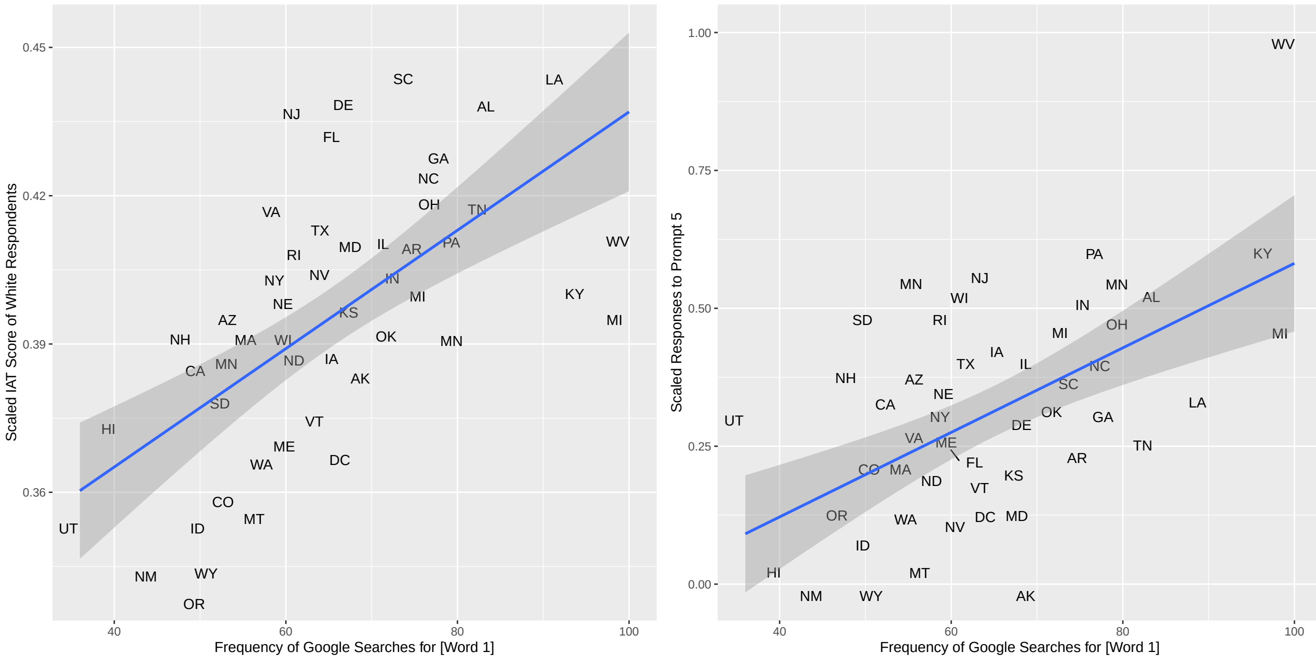
This analysis uses the concentration of Google searches containing racial epithets as a proxy measurement of the level of racial animus in an area. Originally developed by Stephens-Davidowitz (2014) to understand the link between racial animus and the under-performance of black candidates in national elections, I argue that this measure has significant advantages over traditional survey-based methods as it is not subject to the same social desirability biases that confound traditional measures; and provides a rich, regularly-sampled repeated measure of racial animus.

I argue that this is an

The core assumption of this strategy is that Google searches for the word [Word 1] reflect underlying racial animus in an area. If readers find this assumption unconvincing, then they will have little reason to accept the conclusions of this analysis.

First, Google searches do not suffer from the same social censoring as traditional measures of public opinion that rely on face-to-face or over-the-phone interviews. Overt expressions of racism are no longer socially palatable in the U.S., Social desirability bias is a pressing concern when it comes to measuring racial animus; research has repeatedly demonstrated that (Kuklinski, Cobb, and Gilens, 1997)

This measurement approach has an advantage over traditional survey-based measures of racial animus in that it is less subject to a social desirability bias; "Google searchers are online and likely alone, both of which make it easier to express socially taboo thoughts (Kreuter et al.,



2009)" (Stephens-Davidowitz, 2014, p. 26). Further, it provides a high-resolution set of data that would be prohibitively expensive to collect from a traditional survey, especially given that the difference-in-differences approach requires a repeated survey comparable across multiple time periods.
[1]

As such, I give several reasons to suggest that Google trends data can be used to measure racial animus.

A pressing concern is that Google searches for "[Word 1](s) " may not actually capture the extent of racial bias in an area, but simply reflect users learning about the term. In fact, "definition of [Word 1] " and "what does [Word 1] mean" are both among the top 5 search queries related to the "[Word 1] ". These queries suggest that many who search for the term are searching out of curiosity to investigate the term.

This is not to suggest that searches for the term do not capture any variation in racial animus: among the top 10 most searched related queries to the term [Word 1]'s are "I don't like [Word 1]'s ," "fuck the [Word 1]'s ," and "ship those [Word 1]'s back."

The concern that Google Searches for racial slurs may largely reflect curiosity about the term is valid. Subject to data availability, I suggest controlling for the frequency of searches for the definitions of these terms in each area, to try and isolate the effect of Sinclair media entering a market on searches expressing "hardcore" racial animus rather than curiosity.

4 Methods

4.1 Tools Used

Surveys of major social science journals routinely fail to reproduce the findings of a plurality or majority of papers from the supplementary code and data provided (Nuijten, Hartgerink, et al.,

[1] Stephens-Davidowitz, 2014 evidences this claim by reporting statistics for pornography searches. Over the past 16 years, the number of searches for "porn" and "news" are commensurate, yet only 14% of GSS respondents tell the GSS they have visited a pornographic website in the past 30 days.

Figure 2: Sinclair News Anchors Reading a “Must-Run” Script (May 2018)

(a) Images of 30 of 210 Sinclair Station Hosts Reading a Must-Run Script (Burke, 2018)

> **(A):** But we’re concerned about the troubling trend of irresponsible, one sided news stories plaguing our country. The sharing of biased and false news has become all too common on social media.
>
> **(B):** More alarming, some media outlets publish these same fake stories... stories that just aren’t true, without checking facts first.
>
> **(A):** Unfortunately, some members of the media use their platforms to push their own personal bias and agenda to control ’exactly what people think’...This is extremely dangerous to a democracy.

(b) Transcript of Segment (Cohen, 2018)

2015; Nuijten and Polanin, 2020; Eubank, 2016).

Failures to replicate are often due to coding errors or mistakes in transcribing the results of a calculation into a published manuscript (Eubank, 2016, p. 276).

I use Kintr to integrate statistical calculations into the paper, eliminating the possibility of transcription errors (Xie, 2014). To ensure that the methods of this paper have been properly implemented and the finding are reproducible, I tested the analysis routines using the *testthat* package in R (Wickham, 2011) and the *unittest* module in Python (Van Rossum and Drake, 2009). But I won’t make you take my word for it – I provide a Docker image with the reproducibility materials to ensure others can replicate the calculations on their own systems (Merkel, 2014; Boettiger, 2015). The net result is “one-click reproducibility” (Nüst et al., 2020); readers can reproduce this exact paper with the push of a button from the linked materials. [2]

4.2 Preregistration

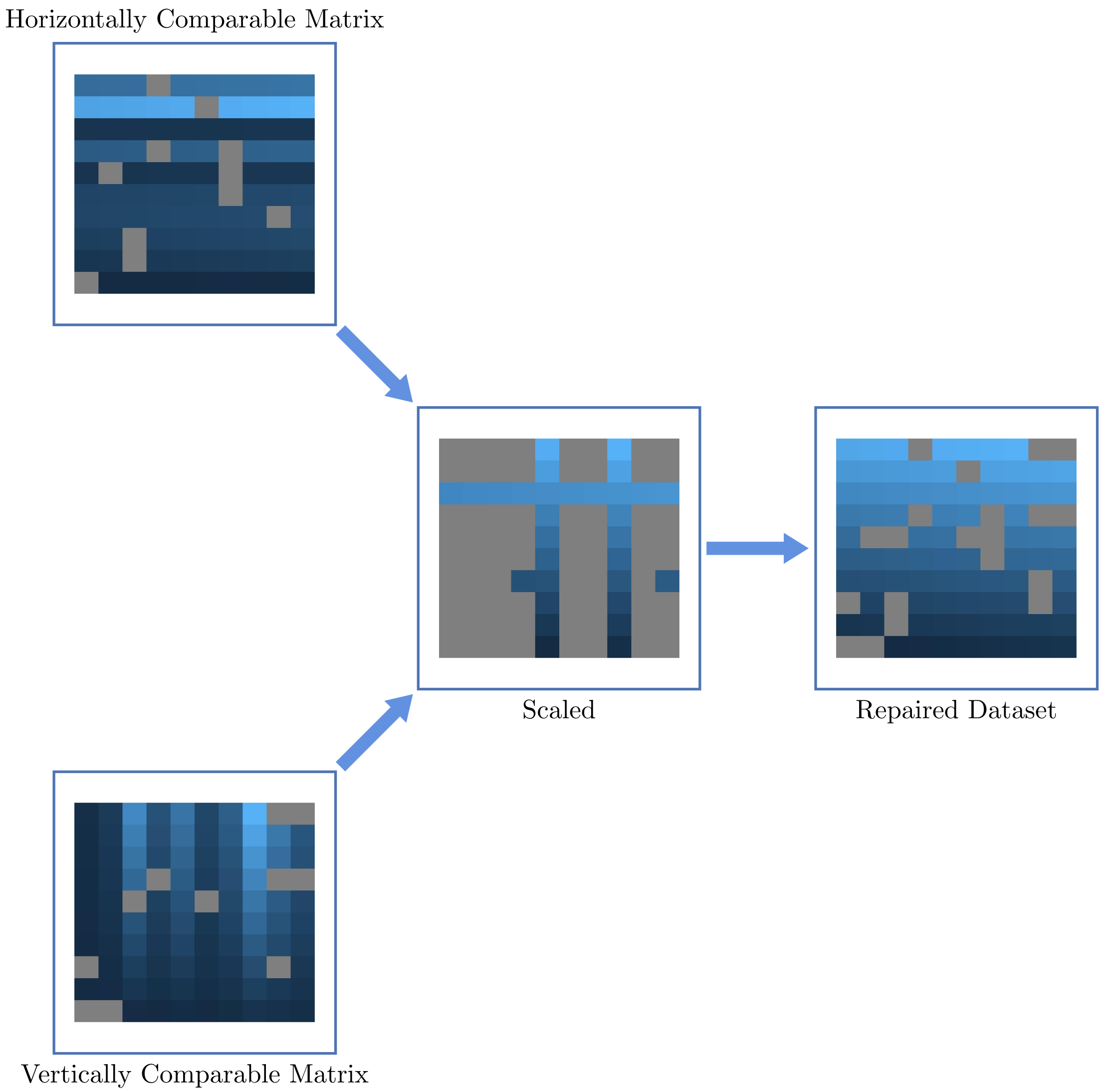
To avoid the possibility of fitting hypotheses to the data after results are known, I created a preregistration plan of my analysis. The plan can be seen in section **??**.

I have made one significant deviation from the preregistration plan. In my preregistration, I describe a strategy to back out a ratio-level measure of the number of searches for [Word 1] in an area from Google trends data. This strategy is based on a misunderstanding of the format of Google trends data, and does not actually produce the desired measure.

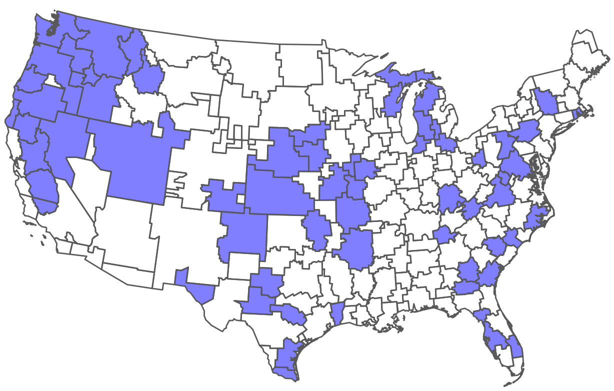
In the analysis I perform, I correct this mistake. I describe the correct scaling procedure in section **??**.

[2]Replication materials available here. By default, the aggregation

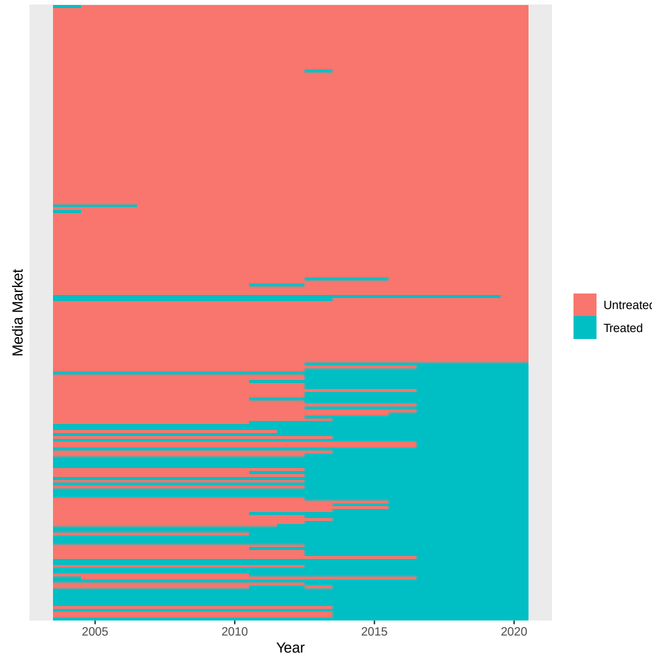
Figure 3: Illustration of Scaling Algorithm



(a) Media Markets Sinclair Bought or Sold a Station in between 2004-2020. DMA Boundaries From Hill, 2015



(b) Media Markets by Sinclair Ownership Status, Time



5 Results

$$\text{Racially Charged Search Rate} = \beta_1(\text{ Sinclair Present }) + \beta_2(\text{ DMA fixed effects }) + \beta_3(\text{ year fixed effects })$$

Table 1: Fixed-Effect Model Results

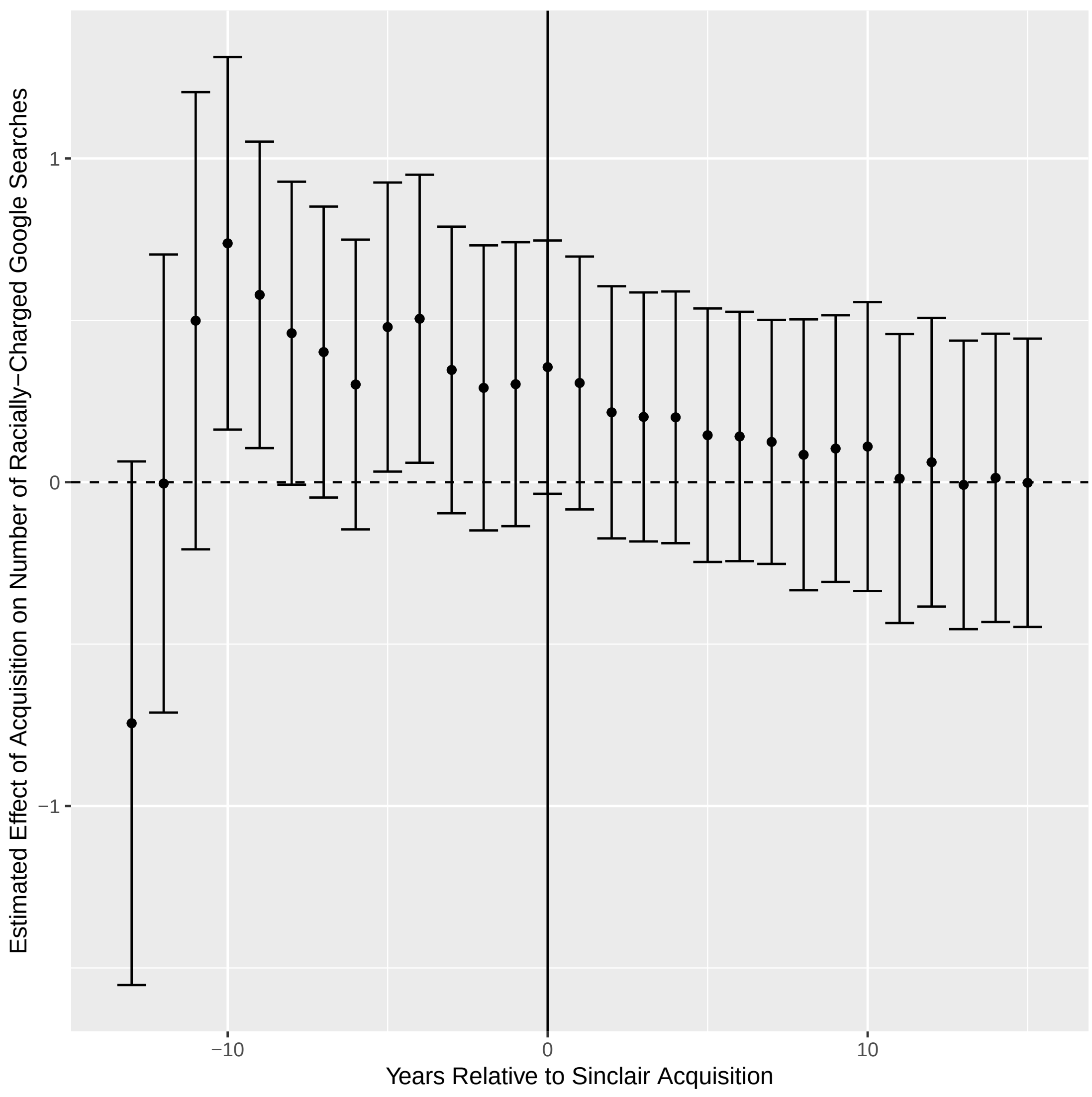
	Dependent variable:	
	Frequency of Google Searches for [Word 1]	
	(1)	(2)
Sinclair Present	-0.122^{*}	-0.068
	(0.065)	(0.107)
Constant	-0.212	41.959
	(0.234)	(126.128)
Year Fixed Effects	Yes	Yes
Region Fixed Effects	Yes	Yes
Region Time Trends	No	Yes
Observations	3,570	3,570
R^2	0.240	0.309
Adjusted R^2	0.188	0.214
Residual Std. Error	0.901 (df = 3343)	0.887 (df = 3134)
F Statistic	4.668^{***} (df = 226; 3343)	3.229^{***} (df = 435; 3134)
Note:		*p<0.1; **p<0.05; ***p<0.01

5.1 Indentification Asssumption

In this section, I test the indefication assumption, the assumption that the treated and control units would have the outcomes if the treatment were absent.

$$\text{Racially Charged Search Rate} = \beta_1(\text{ Sinclair Present }) + \beta_2(\text{ DMA fixed effects }) + \beta_3(\text{ year fixed effects }) + \beta_4(\text{Year / D}$$

Figure 5: Fixed-Effects Estimates of the effect of Sinclair Acquisition on Rate of Racially Charged Google Searches



Code	Word
Word 1	nigger

A Codings for Offensive Words

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B Code In This Document

C Web Scraping Code

C.1 Master Web Scraping Script

```python
#!/usr/bin/python
import glob
import os
import pickle as pkl
from between_regions import between_reigion_many
from in_region import in_region
from utils import itr_split_overlap
import tqdm


def extract_keywords(filename):
    with open(filename, "r") as f:
        keywords = f.read().splitlines()
    return keywords


def get_basename(filename):
    name_w_ext = os.path.basename(filename)
    basename = os.path.splitext(name_w_ext)[0]
    return (basename)


def run_keywords(name, keywords):
    regions = pkl.load(open("data/dma_abbreviations.pkl", "rb"))
    filename = f"data/google_trends_data/{name}_time_serires.csv"
    with open(filename, "w") as f:
        f.write("row,date,score,ispartial,code,term\n")
        for keyword in keywords:
            for region in tqdm.tqdm(regions):
                df = in_region(keyword, region, True, timeframe="all")

```

```python
                if df is not None:
                    df.to_csv(f, header=False)

    filename = f"data/google_trends_data/{name}_between_regions.csv"
    with open(filename, "w") as f:
        df = between_reigion_many(itr_split_overlap(keywords, 5, 1),
                                  censor=True,
                                  timeframe="all",
                                  geo="US",
                                  gprop="")
        df.to_csv(f, header=True)


if __name__ == "__main__":
    keyword_files = sorted(glob.glob("data/keywords/*.csv"))
    base_names = [get_basename(filename) for filename in keyword_files]
    keywords = [extract_keywords(filename) for filename in keyword_files]
    first = (list(zip(base_names, keywords)))[0]
    run_keywords(first[0], first[1])
```

C.2 Collecting Data for Between-Region Comparisons

```python
#!/usr/bin/env python
from pytrends.request import TrendReq
from utils import censor_string
import pandas as pd


def between_region(query, censor, **kwargs):
    pytrends = TrendReq(hl='en-US', tz=360)
    pytrends.build_payload(query, cat=0, **kwargs)
    df = pytrends.interest_by_region(resolution='DMA',
                                     inc_low_vol=True,
                                     inc_geo_code=True)
    df = df.set_index("geoCode")
    df.index.name = 'code'
    if censor:
        df = df.rename(censor_string, axis="columns")
    return (df)


def between_reigion_many(iterable, censor, **kwargs):
    iterable = iter(iterable)
    chunk1 = next(iterable)
    df1 = between_region(chunk1, censor, **kwargs)

    for chunk in iterable:
        chunk2 = chunk
        shared = list(set(chunk1) & set(chunk2))[0]
        if censor:
            shared = censor_string(shared)
        df2 = between_region(chunk2, censor, **kwargs)

        mean1 = df1[shared].mean()
        mean2 = df2[shared].mean()
        normaliation_factor = mean1 / mean2

        df2 = df2 * normaliation_factor
        df2 = df2.drop(columns=[shared])

        df1 = df1.join(df2)

        chunk1 = chunk2

    return (df1)


def create_v_df(term, year):
    timeframe = f"{year}-01-01 {year}-12-31"
    df = between_region([term], False, timeframe=timeframe, geo="US")
    df = df.rename(columns={term: str(year)})
    return df


if __name__ == "__main__":
    dfs = tuple(create_v_df("hello", year) for year in range(2004, 2021))
```

```
    df_c = pd.concat(dfs, axis=1)

    df_c.to_parquet("v_matrix.parquet")
```

C.3 Collecting Within-Region Data

```
#!/usr/bin/python
from pytrends.request import TrendReq
from utils import censor_string
import time
import pandas as pd
import re
import pickle as pkl


def in_region(query, region, censor, **kwargs):
    """ Returns a set of data showing the popularity of a search term over time

    :query: The search term that time-series data is collected for
    :region: The geographic region to retrieve time-series data for.
    :censor: boolean should the search terms be censored?
    :**kwargs: kwargs to be passed to pytrends.build_payload()
    :returns: DataFrame giving time-series data for the popularity of a
        search term in a given region

    """
    pytrends = TrendReq(hl='en-US', tz=360)
    try:
        pytrends.build_payload(kw_list=[query], geo=f"{region}", **kwargs)
        df = pytrends.interest_over_time()
        if df.empty:

            df = pd.DataFrame()
            df['date'] = pd.period_range(start='2004-01-01',
                                         end='2021-01-01',
                                         freq='M').to_timestamp()
            df['n'] = 0
            df['ispartial'] = pd.Series([True]).bool()

        else:

            df.columns = ["n", "ispartial"]
            df.index.name = 'date'
            df.reset_index(inplace=True)

        df["query"] = query
        df['code'] = re.findall("\d+", region)[0]
        if censor:
            df["query"] = df["query"].apply(censor_string)

        return df
    except:
        if censor:
            print(f"Rate error: {censor_string(query)} in {region}")
        else:
            print(f"Rate error: {query} in {region}")

        time.sleep(60)
        return in_region(query, region, censor, **kwargs)


def to_wide(df):
    """TODO: Turns time-series search popularity data into a 'wide' dataframe to be used in scaling

    :df: 'long' dataframe of search data, as from in_region()
    :returns: 'wide' DataFrame of search data, averaged by year

    """
    print(df['date'])
    df['year'] = pd.DatetimeIndex(df['date']).year
    df['year'] = df['year'].apply(str)
    df = df.groupby(['year', 'code'])["n"].mean()
    df = df.unstack(level=0)
    return (df)

```

```

# with open("data/dma_abbreviations.pkl", "rb") as f:
#     dmas = pkl.load(f)

# dmas = dmas

# in_region_dfs = tuple(
#     in_region("economist", dma, True, timeframe="all") for dma in dmas)
# wide_dfs = map(to_wide, in_region_dfs)
# h_df = pd.concat(wide_dfs).sort_index()
# print(h_df)
```

C.4 Utility Functions

```
#!/usr/bin/python
import itertools as it
import requests
import random


# returns mean of nonzero values in iterator
def mean_nonzero(iterator):
    nonzero = tuple(filter(lambda x: x != 0, iterator))
    if len(nonzero) == 0:
        return None
    elif None in nonzero:
        return None
    else:
        return sum(nonzero) / len(nonzero)


# Returns list of N random words from MIT dictionary
def random_words(n):
    word_site = "https://www.mit.edu/~ecprice/wordlist.10000"

    response = requests.get(word_site)
    words = response.text.splitlines()

    keywords = random.sample(words, n)

    return (keywords)


# Tests if computer is connected to internet (used in tests)
def connected():
    url = "http://google.com"
    timeout = 5
    try:
        requests.get(url, timeout=timeout)
        return (True)
    except (requests.ConnectionError, requests.Timeout):
        return (False)


# Censors strings so that senstive words aren't uploaded to github / used in
# scripts
def censor_string(string):
    return (string[0] + "_" * (len(string) - 2) + string[-1])


# credit to Ilja Everila for this implimentation
# https://stackoverflow.com/questions/48381870/a-better-way-to-split-a-sequence-in-chunks-with-overlaps
def itr_split_overlap(iterable, size, overlap):

    if overlap >= size:
        raise ValueError("overlap must be smaller than size")

    itr = iter(iterable)

    next_ = tuple(it.islice(itr, size))

    yield next_

    prev = next_[-overlap:] if overlap else ()

```

```
    while True:
        chunk = tuple(it.islice(itr, size - overlap))

        if not chunk:
            break

        next_ = (*prev, *chunk)
        yield next_

        if overlap:
            prev = next_[-overlap:]
```

D Analysis Code

```
#!/usr/bin/Rscript
# Load Libraries for Analysis
library(tidyverse)
library(lubridate)
library(broom)
# Load utility functions
source("utils.R")

search_data <- read_csv("data/google_trends_data/word_1.csv") %>%
  pivot_longer(-code, names_to = "year", values_to = "word1") %>%
  mutate_all(as.numeric)

stopifnot(nrow(search_data) == 3570)
stopifnot(all(!is.na(search_data)))

write_csv(search_data, "../data/google_trends/word1.csv")

sinclair_data <- read_csv("../data/clean_sinclair_data.csv")
stopifnot(nrow(sinclair_data) == 3570)
stopifnot(all(!is.na(sinclair_data)))

# search_data <- search_data %>%
#   dplyr::select(-data) %>%
#   distinct(term, code, year, .keep_all = TRUE) %>%
#   pivot_wider(names_from = term, values_from = score) %>%
#   mutate(overall_score = rowSums(across(everything()), na.rm = T))
dma_names <- read_csv("data/dma_list.csv")
stopifnot(nrow(dma_names) == 210)

full_data <- search_data %>%
  right_join(sinclair_data) %>%
  full_join(dma_names) %>%
  filter(year != 2021) %>%
  group_by(code) %>%
  mutate(years_before = years_before(sinclair_present)) %>%
  ungroup() %>%
  mutate(sword1 = (word1-mean(word1))/sd(word1)) %>%
  mutate(years_before = relevel(as.factor(years_before),"-99"))

stopifnot(nrow(full_data) == 3570)
stopifnot(all(!is.na(full_data)))

write_csv(full_data, "../data/full_data.csv")

model_1 <- lm(sword1 ~ as.factor(year) + as.factor(code) + sinclair_present, data = full_data
    )
model_1 %>% summary()

model_2 <- lm(sword1 ~ as.factor(year) + as.factor(code) + year:as.factor(code)+ sinclair_
    present, data = full_data)
model_2 %>% summary()

model_3 <- lm(sword1 ~ as.factor(year) + as.factor(code) + as.factor(years_before), data =
    full_data)
model_3 %>% summary()

model_3 %>%
  tidy() %>%
  filter(grepl("years_before", term)) %>%
  mutate(term = as.numeric(gsub("[^0-9\\-]+", "", term))) %>%
  ggplot(aes(x = term, y = estimate)) +
```

```
  geom_point() +
  geom_errorbar(aes(ymin = estimate - 1.96 * std.error, ymax = estimate + 1.96 * std.error)) +
  geom_hline(aes(yintercept=0), linetype=2) +
  geom_vline(aes(xintercept=0))
```

D.1 Utility Functions

```
#!/usr/bin/Rscript
censor_string <- function(string) {
  substr(string, 2, nchar(string) - 1) <- paste0(rep("_", nchar(string) - 2), collapse = "")
  names(string) <- NULL
  return(string)
}
censor_string <- Vectorize(censor_string, USE.NAMES=F)

years_before <- function(bool) {
  if (any(bool)) {
    out <- numeric(length = length(bool))
    start <- min(which(bool))

    before <- (seq(start, 1) - 1) * -1
    if (start != length(bool)) {
      after <- seq(1, length(bool) - start)
    } else {
      after <- c()
    }


    out <- c(before, after)
  } else {
    out <- rep(-99, length(bool))
  }

  return(out)
}
```

E Unit tests

E.1 For Python Code

```
#!/usr/bin/python
import unittest
import pandas as pd
from between_regions import between_region
from utils import connected


@unittest.skipIf(not connected(), "not connected to the internet")
class TestBetweenRegion(unittest.TestCase):
    def test_between_region_uncensored(self):

        result_1 = between_region(["socks"],
                                  censor=False,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
                                  gprop="")

        result_2 = between_region(["socks", "shoe", "fish"],
                                  censor=False,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
                                  gprop="")

        expected_1 = pd.read_parquet(
            "tests/test_data/between_region_1_uc.parquet")
        expected_2 = pd.read_parquet(
            "tests/test_data/between_region_2_uc.parquet")

        self.assertTrue(expected_1.equals(result_1))
        self.assertTrue(expected_2.equals(result_2))

    def test_between_region_censored(self):
        result_1 = between_region(["socks"],
```

```
                                  censor=True,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
                                  gprop="")

        result_2 = between_region(["socks", "shoe", "fish"],
                                  censor=True,
                                  timeframe="2016-12-14 2017-01-25",
                                  geo="US",
                                  gprop="")

        expected_1 = pd.read_parquet(
            "tests/test_data/between_region_1_c.parquet")
        expected_2 = pd.read_parquet(
            "tests/test_data/between_region_2_c.parquet")

        self.assertTrue(expected_1.equals(result_1))
        self.assertTrue(expected_2.equals(result_2))
```

```
#!/usr/bin/python
import unittest
from utils import itr_split_overlap, censor_string


class TestItrSplitOverlap(unittest.TestCase):
    def test_itr(self):
        test_list = ["one", "two", "three", "four", "five"]

        expected_result = [('one', 'two'), ('two', 'three'), ('three', 'four'),
                           ('four', 'five')]
        self.assertEqual(expected_result,
                         list(itr_split_overlap(test_list, 2, 1)))

        expected_result = [('one', 'two', 'three', 'four'),
                           ('two', 'three', 'four', 'five')]
        self.assertEqual(expected_result,
                         list(itr_split_overlap(test_list, 4, 3)))

    def test_exceptions(self):
        with self.assertRaises(ValueError):
            test_list = ["one", "two", "three", "four", "five"]

            list(itr_split_overlap(test_list, 2, 3))


class CensorString(unittest.TestCase):
    def test_censor(self):
        self.assertEqual("h_y", censor_string("hey"))
        self.assertEqual("f____r", censor_string("fender"))
        self.assertEqual("fr", censor_string("fr"))
```

E.2 For R Code

```
library(testthat)
source("../../utils.R")

test_that("censor string works", {
      expect_equal(censor_string("hey"),"h_y")
      expect_equal(censor_string("hy"),"hy")
      expect_equal(censor_string("watermelon"),"w________n")
      expect_equal(censor_string("fantastic"),"f_______c")
})

test_that("censor string vectorized correctly", {
      expect_equal(censor_string(c("hello","there")),c("h___o","t___e"))
      expect_equal(censor_string(c("watermelon","paper")),c("w________n","p___r"))
})

test_that("years before works", {
  expect_equal(years_before(c(F, F, F, T, T)), c(-3, -2, -1, 0, 1))
  expect_equal(years_before(c(F, F, F, F, T)), c(-4, -3, -2, -1, 0))
  expect_equal(years_before(c(T, T, T, T, T)), c(0, 1, 2, 3, 4))
})
```