Challenges in the Visualization of Sleep Deprivation across the US

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Abstract

Sleep deprivation is a wide-spread public health issue in the United States and many other countries. Rising awareness of the issue has led to large-scale epidemiological efforts to measure the prevalance and cost of the issue. Visualization of this information is crucial for informing policy and planning targeted interventions to populations in need, however, visualizing the data often involves a large number of decisions on the preprocessing of the data which can influence the conclusions made. This brief report touches on a few of these challenges, and provides some recommendations for transparency.

Introduction

Approximately 1/3 of the population of the United States reports having less sleep on average than the recommended 7 hours a night (CDC, 2011; Liu, 2016). Chronic sleep deprivation is considered a serious public health issue, as insufficient sleep is associated with increased workplace related accidents (Dinges, 1995; Rosekind et al., 2010), obesity (Gangwisch, Malaspina, Boden-Albala, & Heymsfield, 2004; Knutson, Spiegel, Penev, & Van Cauter, 2004), drowsy driving (J. Horne & Louise, 1995; Howard et al., 2004), cardiovascular disease (Ayas et al., 2003; Mullington, Hacch, Toth, Serrador, & Meier-Ewert, 2009), and a variety of other risks/conditions. Sleep deprivation is also correlated with decreased decision making (Harrison & Horne, 2000) and sustained attention (Lim & Dinges, 2000), which may provide one explanation for some of the associated behavioral detriments.

There have been sizable efforts on the part of the Centers for Disease Control (CDC) and National Sleep Foundation (NSF) to better understand the prevalance and costs of sleep deprivation through large-scale surveys across the United States. These surveys provide critical information for future policy and planning targeted interventions, and have led to some preliminary suggestions including employers tailoring shift-systems design (CDC, 2012), greater involvement by health-care providers (CDC, 2009), limiting active technology use before sleep (Gradisar et al., 2013), and general increased public awareness of sleep deprivation.

Communicating complex spatial data, such as nation-wide polls, requires a number of decisions and pre-processing steps before creating the final visualizations. This preliminary work can have large effects on the final product, leading to potentially different conclusions. The purpose of this brief report is to outline a non-exhaustive list of practices which would help improve the transparency and clarity of the final report employing these visualizations.

Data

For this brief report we will the 2009 Behavioral Risk Factor Surveillance System (BRFSS) results collected by the CDC. The BRFSS is a yearly survey intended to measure health related behaviors and demographics such as tobacco use, seatbelt use, sleep related habits, etc. The 2009 BRFSS was collected through landlines only, with cellphones being added in 2011 to the survey sample. A total of 432,607 records were collected in this data set across 2231 of the total 3109 counties in the contiguous United States. Observations for which the sleep deprivation question, county, or state were missing/refused to respond/didn't know the answer were removed, leaving a total of 2231 counties and 377,273 records. The sleep related question that will be used here is presented below;

- "During the past 30 days, for about how many days have you felt you did not get enough rest or sleep? (number of days)"
- Response Options:
    - 0-30 days
    - Refuse to respond
    - Don't know
    - Missing / Not asked

This dataset and question were selected due to their use in Grandner et al. (2015), which will allow for some conrete discussion points and comparisons. These criticisms are in no way meant to be a statement against any of the authors or the CDC in general. The responses to this question were dichotomized, with participants reporting greater than 14 days of insufficient sleep being categorized as sleep deprived. This cutoff was chosen based on its use in previous research (Grandner et al., 2015; Strine & Chapman, 2015) and the practical significance of it found in Edinger et al. (2011).

Visualization Challenges

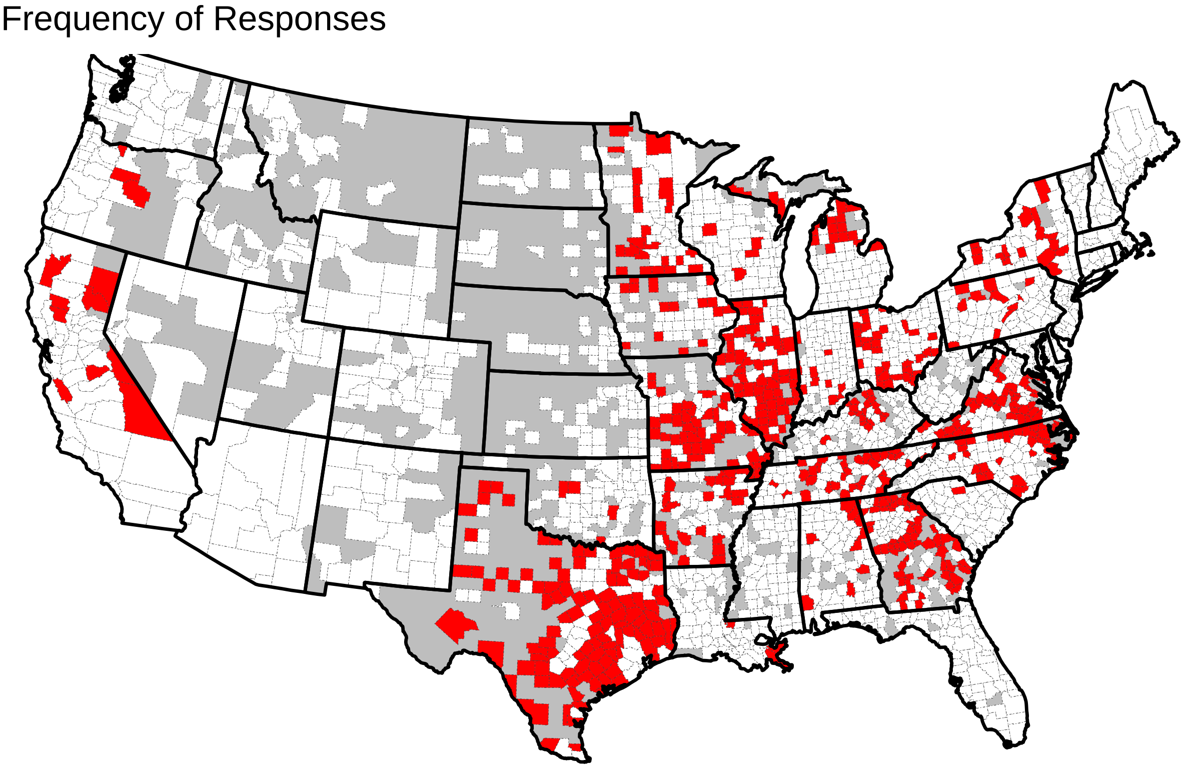
Dichotimization

It is a common practice in the sleep deprivation literature to dichotomize a continuous measure of sleep to seperate sleep deprived and non-sleep deprived conditions. Dichotomizing the variable provides an easier interpretation, and helps circumspect the issue of nonlinearity between hours of sleep and impact on behavior. The cost of dichitomization is a loss of information through simplifying the continuous measure, resulting in a lower statistical power, and the selection of the cutoff point is often arbitrary and can impact the final results. Comparing the analysis across a range of cutoff points can help illuminate whether the final result is sensitive to modest changes in the cutoff points, providing context to the reader on how confident to be in the interpretation of the results.

Sample Size

The BRFSS is primarily concerned with state level estimates of the population, however, data collection can also be broken down into a county level analysis. This additional granularity can be useful in interpreting regional effects, or where a state level aggregation may not be representative (such as California, where significant differences may exist between the north and south). When fragmenting the sample into small bins one should be wary of differences in the sample size of each county, particularly when dealing with binary data which only becomes asymptotically normal around $n > 30$. The smaller sample size counties may display more extreme results, resulting in patterns that could be a function of both the volatile sample size and the parameter of interest, rather than simply the parameter of interest.

For example, below is a plot of the counties with n < 30 (red), counties with n > 30 (white), and counties with no data (grey).



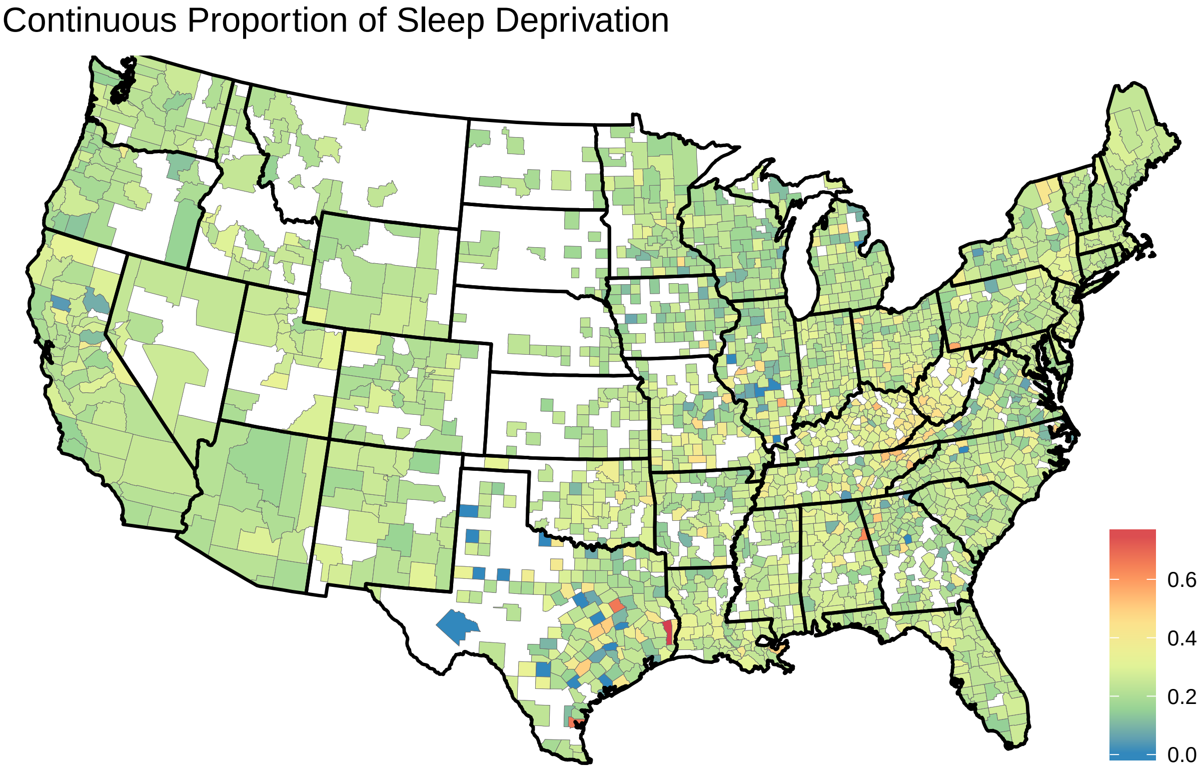
Clear patterns can be seen in the regions of insufficient data, and strong similarities are present with the regions in the uppermost quintile of sleep deprivation in Grandner et al. (2015).

Missing Data

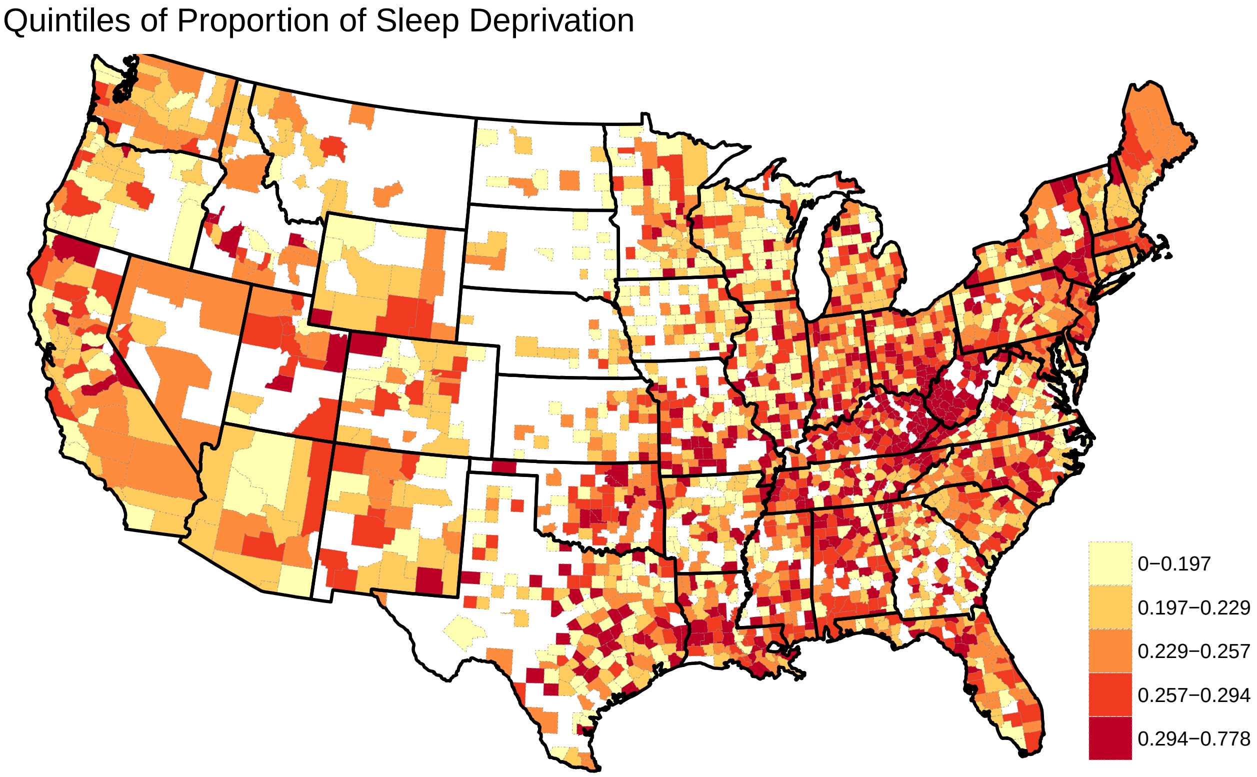
The reasons for and types of missing data are critical for the generalizability of the results. It can be all too easy to simply remove all missing data and move forward, assuming its only impact is a diminshed sample size. However this may not be the case depending on why the data is missing; whether the interviewer ran out of time, the indiividual didn't know the answer, or they refused to answer are all very different reasons to not have a response. The distribution of these causes may differ across subsamples resulting in estimates biased toward certain subpopulations and resulting in a loss of generlizability of results. The response rate by region to the survey is also an important consideration, as that will also influence the representiviveness of the sample for the general population. Within small sample sizes, such as a county level anaylsis, most of these factors are unable to be accounted for, requiring instead a clear description of their limitations.

Quintiles

When visualizating continuous data across a large amount of space, such as a county level analysis of the United States, it can often become challenging to see differences between regions due to the density of the space and range of the data. Under these circumstances, quintiles are often used to break the data into seperate equally sized ordered bins in order to make patterns more visible. The cost of using quintiles is that it comes at a loss of information and interpretability. As with dichotomization, the ranges and distribution of data within the bins disappears, and the bins can make differences look larger than they are if the viewer isn't attentive to the range for each bin. Displaying the original continuous variable along with the quintile helps ensure that the scale of differences can still be easily interpreted, while still allowing for patterns to be more visible.



This plot shows us that while there are differnces across regions, most of these differences are fairly small. Texas shows the most variability among the states, however this may be due to the high proportion of low sample size counties as seen in the previous plot.



The quintile plot illustrates that the Appalachian region tends to have larger proportions of sleep deprivation than othe regions, and that there is a large amount of heterogeniety within states. The variablity within states for sleep deprivation, for example in California, tells us that state level aggregates may miss out on some regional trends. It is important to note however that as quintiles are splitting the data into equal size bins, the ranges within each bin will almost certainly be differnt. Here the first and last bin have a large range, while the center bins have a very small spread. Based on the plot alone we cannot tell what the distribution of the individual bins are, for example if we have one observation at at extreme value and the rest clustered elsewhere, or if they are evenly distributed within the range. The previous unbinned plot allows us to answer these questions easily.

Reproducibility

There has been a rising awareness in the general issue of reproducibility in science. This has resulted in an increased push for transparency in the analyses of data and making data publicly available. It is often the case that all of the relevant information cannot be included in a report due to the need for brevity; while this is a sensible constraint for general communication, it can result in a lack of transparency for how the results were created. While writing this report I was unable to recrease the results in Grandner et al. (2015), resulting in similar but different quintile plots. This could be due to a variety of reasons, including a mistake on one of our parts or different decisions in the preprocessing of the data that weren't clearly described. Providing the code used to create the report, such as is done here, can allows anyone to recreate and follow the path for the final results in the report. Creating an appendix with the finer details allows for the desired brevity while still maintaining transparent process.

Conclusion

Presenting a large amount of information in a condensed format comes with many challenges, and the need for simplification. This simplification often comes at some cost, but is required to have an interpretable visualization. The need for brevity may often prevent the analyst from displaying all of the relevant information in a short-hand report, however, the inclusion of such information in a second more detailed report would improve the transparency and clarity with which the findinngs are displayed, and may help ensure the appropriate interpretation of the final result.

Code

```r
BRFSS_geoextraction <- function(filepath, id = "county", position,
                                extraction, contiguous=TRUE,latlong=TRUE,
                                func = function(x) {mean(x, na.rm=T)}) {
    # Error Catching
    if(!grepl("state", tolower(position[1]))){stop("State must be first position.")}
    if(!is.character(filepath)) {stop("Filepath must be character")}
    if(!is.character(position)) {stop("Position must be character")}
    if(!is.character(extraction)) {stop("Extraction variable must be character name.")}
    if(length(extraction)!=1) {stop("Function currently only accepts one extracted var.")}
    if(!id %in% c("county", "state")) {stop("ID must be county or state.")}
    if(!is.function(func)){stop("Func must be a function.")}
    if(id == "county" & length(position) != 2) {
        stop("County level requires position to have State and County varialbe names. ")
    }
    # Setup
    require(SASxport)
    require(dplyr)
    require(maps)
    require(stringr)
    require(ggplot2)
    strsplit2 <- function(x, char, index){
        unlist(strsplit(x, char))[index]
    }
    clear_labels <- function(x) {
        if(is.list(x)) {
            for(i in 1 : length(x)) class(x[[i]]) <- setdiff(class(x[[i]]), 'labelled')
            for(i in 1 : length(x)) attr(x[[i]],"label") <- NULL
        }
        else {
            class(x) <- setdiff(class(x), "labelled")
            attr(x, "label") <- NULL
        }
        return(x)
    }
    # Read Data
    data <- read.xport(filepath) %>%
        clear_labels(.)
    # Subset
    keep <- c(position, extraction)
    keep.states <- if(contiguous) {
        c(15, 2, 66, 72, 78)
    } else {c()}
    # Remove Excess
    data2 <- data %>%
        select(one_of(keep)) %>% # Select columns of interest
        filter(!(!!rlang::sym(position[1])) %in% keep.states) %>% # Select States
        filter(!(is.na(!!rlang::sym(position[1])))) # remove missing states
    if(id == "county"){
        data2 <- data2 %>%
            filter(!(!!rlang::sym(position[2])) %in% c(777,999)) %>%
            filter(!(is.na(!!rlang::sym(position[2])))) %>%
            mutate(FIPS = as.numeric(paste0(
                !!rlang::sym(position[1]),
                str_pad(!!rlang::sym(position[2]),3,pad = "0"),
                sep = "")
            ))
    } else {
        data2 <- data2 %>%
            mutate(FIPS = !!rlang::sym(position[1]))
    }
    # Get FIPS Codes
    if(id == "county") {
        data(county.fips)
        county.fips$polyname <- sapply(county.fips$polyname, function(x) {
            unlist(strsplit(x, ":"))[1]
        })
        county.fips <- unique(county.fips)
        fips.codes <- county.fips
    } else {
        data(state.fips)
        state.fips$polyname <- sapply(state.fips$polyname, function(x) {
            unlist(strsplit(x, ":"))[1]
        })
        state.fips <- unique(state.fips)
        fips.codes <- as.data.frame(state.fips)
    }
    varname <- paste0(extraction, ".f", sep = "")
    # Merge By FIPS
    data3 <- data2 %>%
        left_join(fips.codes, by = c("FIPS" = "fips")) %>% # Get location string
        group_by(polyname,FIPS) %>% # State/County-wise operations
        summarize(!!varname := func(!!rlang::sym(extraction)), # Function
                  n = sum(!is.na(!!rlang::sym(extraction))), # Frequency of response
                  prop.responded = sum(!is.na(!!rlang::sym(extraction)))/n()) %>%
        filter(!is.na(!!rlang::sym(varname))) %>% # Remove Missing
        mutate(state = strsplit2(polyname, ",", 1)) # Extract state name
    if(id == "county") {
        data3$county <- strsplit2(data3$polyname, ",",2)
    }
    # Merge for coordinates
    if(id == "county"){
        map <- map_data('county') %>%
            mutate(polyname = paste0(region, ",", subregion, sep = "")) %>%
            select(-c(group, order, region, subregion))
    } else {
        map <- map_data('state') %>%
            mutate(polyname = paste0(region, ",", subregion, sep = "")) %>%
            select(-c(group, order, region, subregion))
    }
    if(latlong) {data3 <- left_join(data3, map, by = "polyname")}
    # Output
    data3
}
```

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