American overweight and Multiple Indicators: With Special Focus on different states*

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Abstract

The overweight rate of a country is vital for society. The Behavioral Risk Factor Surveillance System from CDC provides a valuable opportunity to analyze the overweight in America. This paper examines the correlation between multiple physical characteristics with the living habits of Americans and their effect on the overweight in America. Based on my data, I am able to conclude that sleeping time, general health, sex, smoke, age, exercise, drinking alcohol does affect BMI and overweight. By state analysis, we understand that the BMI regional differences exist and the health spending per capita is inversely proportional to overweight.

Introduction

The overweight rate of a country is vital for society and plays an important role in human healthy life. The rising overweight rates in developed countries have brought continuous challenges to their policymakers. The United States of America, as one of the most powerful nations around the world, has been facing the highest overweight rate overall OECD Countries in the past decades(Marion Devaux and Colombo 2017).Over 36.2% of population is overweight in 2017. Further investigation into what causes such a high rate and how the overweight rate impacts individuals' lives is urgent.

A regular daily routine, including sleep and exercise, are essential to a healthy life(Karen R. Segal 1989). We all know that energy is counted in calories. Too many calories in but fewer calories burned will cause energy imbalance and lead to overweight. Highly active and sedentary individuals have a significant difference in their weight if we remove other factors and group them appropriately. Mental health is straightly related to one's overweight as well. Individuals with PTSD were 5% less likely to have healthy diets(Berk-Clark C 2017). In the long run, it will destroy various body functions, resulting in the accumulation of fat in the body, thereby causing overweight. Besides, pregnancy for women and alcohol for men are also very strong relevance to the overweight rate. The recent data and analysis from the mentioned factors conducted in America remain inadequate. There is also a cross-sectional study indicating that heavy drinking could cause excess body weight(Gregory Traversy 2015) and the fact is that 1 gram of alcohol provides 29 kJ energy.

This paper examines the overweight factors all over America. The results suggest that females who drink alcohol, do not smoke, and exercise could have higher BMI. Additionally, sleeping time, age, self-rated health are three numerical factors that increase BMI. Last but not least, the West coast has a lower BMI than the East coast. The remaining part of the paper was organized into four major sections. In the Data section, there is the explanation of the source of the basic data, the data characteristic and exploratory data analysis. By using the multiple linear regression in methodology, I form a model to explain the factors of BMI. Other than that, two maps are used to show the BMI regional differences exist and the health spending per capita is inversely proportional to overweight. The result and discussion include all findings and conclusions in this paper. Finally, an appendix apply some supplementary results.

*Code and data are available at https://github.com/YN7666/sta304-final

Data

The dataset I used in this report is the "Overall version data weighted with _LLCPWT," which was collected by The Behavioral Risk Factor Surveillance System (Atlanta 2020). The Behavioral Risk Factor Surveillance System is an important foundational project supported by the Centers for Disease Control and Prevention's Population Health Surveillance Branch, under the Division of Population Health at CDC's National Center for Chronic Disease Prevention and Health Promotion. BRFSS aims to collect data on health-related risk behaviors in the United States. The target population is 18 years or older who is the householder of their residence in the United States. Every questionnaire has 3 different modules: a core component, a standard set of questions that all states use, optional BRFSS modules that are the questions on specific topics that states elect, and State-added questions that states select but CDC does not edit or track responses from these questions. In the 2020 annual survey, there were 401958 in 53 different states or territories responses. The Data Collection is based on Computer-Assisted Telephone Interview (CATI) systems that could provide an individual questionnaire for the interviewer and finish the procedure in 15 minutes.

The dataset was processed and analyzed in R(R Core Team 2021) and I analyzed all these using R package including: readr(Wickham and Hester 2020), tidyverse(Wickham et al. 2019), kableExtra(Zhu 2021),ggplot2(Wickham 2016), dplyr(Wickham et al. 2021), car(Fox and Weisberg 2019), patchwork(Pedersen 2020) and broom(Robinson, Hayes, and Couch 2022).

Data Characteristic

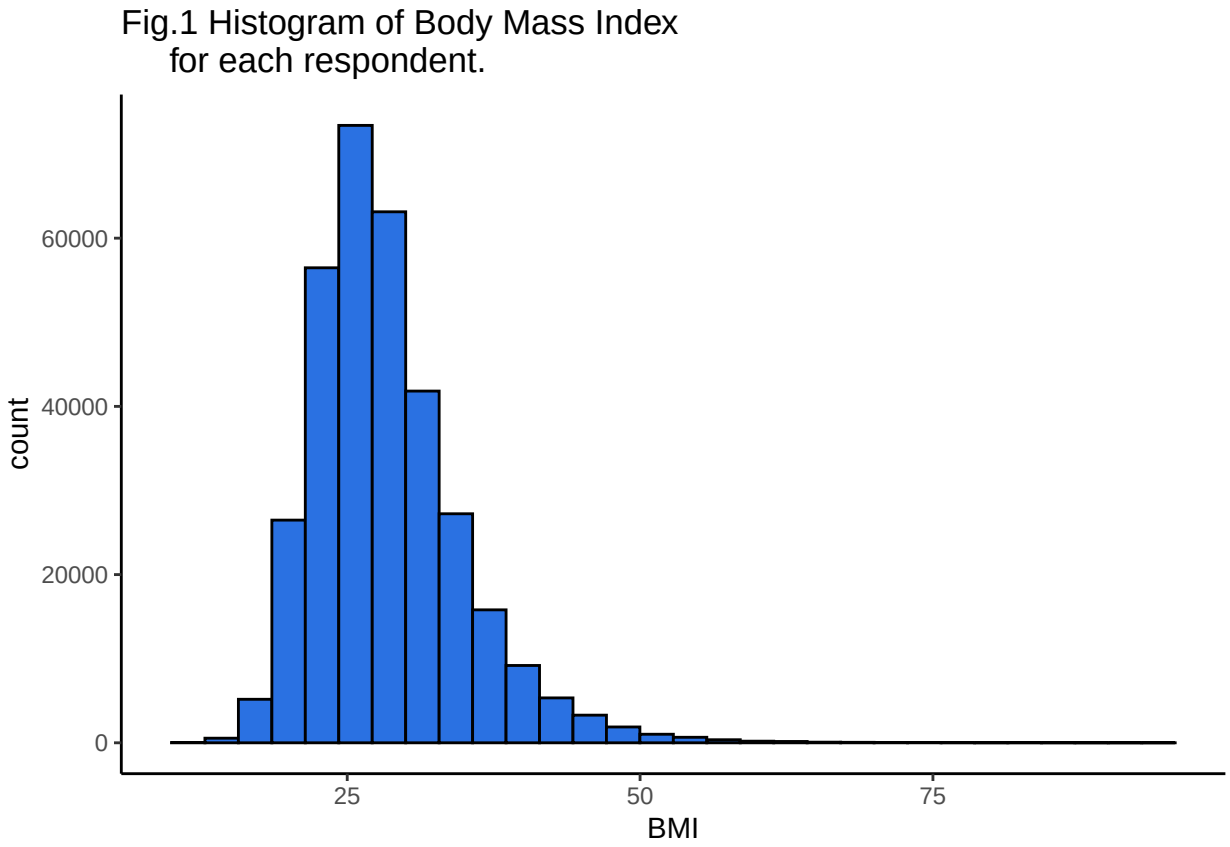


Table 1: summary statistic of Body Mass Index

mean	min	1st Qu.	median	3st Qu.	max	IQR	sd	small_outliers	large_outliers
28.33764	12.02	24.03	27.34	31.46	94.85	7.43	6.374841	41	10421

In total, this dataset spans 280 columns which include 17 different main aspects. After filtering the missing and invalid values, there were 332479 rows remaining and I selected the Body Mass Index as my responsible variable. That is because BMI is defined as weight divided by the square of height. It is an indicator of overall nutritional status, and BMI is statistically highly correlated with body fat. Figure 1 reflects the distribution of the Body Mass Index. The BMI is right-skewed and single-peaked, which means most Americans have a score of BMI under 50, and concentrated around 25. Combined with Table1, the mean is about 28 and the median is 27.34. There are varied large outliers on the right tail and only 41 small outliers on the left tail, which are great facts to justify from the Figure1. Since the height and weight was collected directly from the answer of the respondent and most of the respondent would like to give an inflated height and a lower weight(Frances Shiely 2013), the BMI shows could be smaller than the reality.

Fig.2 Four numerical Indicators

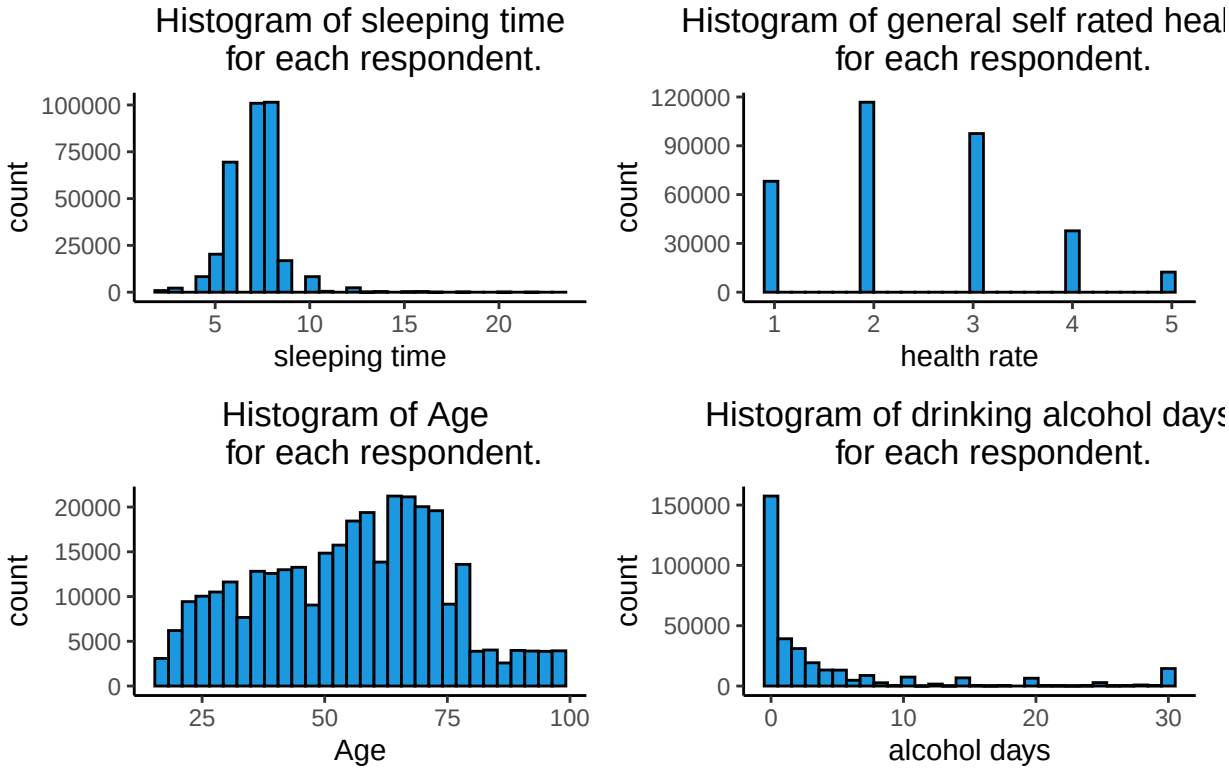
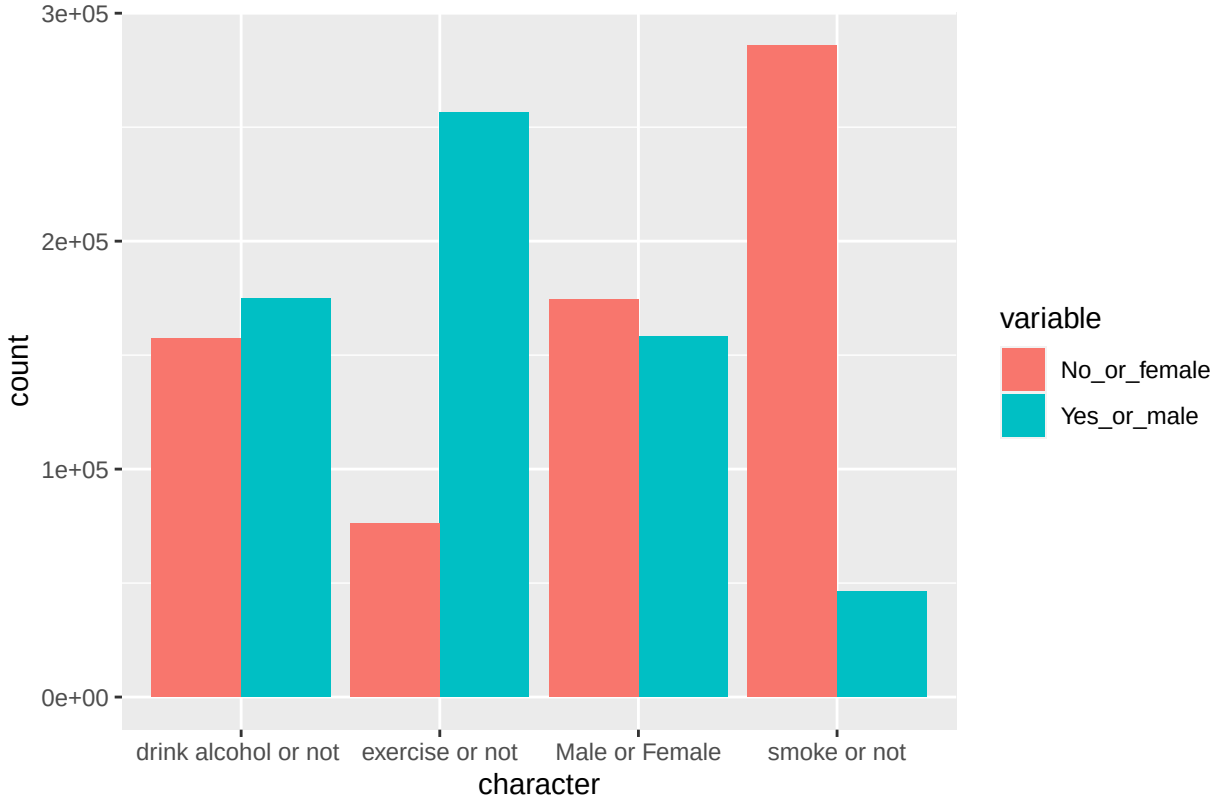


Table 2: summary statistic of Four numerical Indicators

	SLEPTIM1	GENHLTH	X_AGEG5YR	ALCDAY5
	Min. : 2.000	Min. :1.000	Min. :18.00	Min. : 0.000
	1st Qu.: 6.000	1st Qu.:2.000	1st Qu.:40.00	1st Qu.: 0.000
	Median : 7.000	Median :2.000	Median :57.00	Median : 1.000
	Mean : 7.105	Mean :2.426	Mean :55.29	Mean : 3.882
	3rd Qu.: 8.000	3rd Qu.:3.000	3rd Qu.:69.00	3rd Qu.: 4.000
	Max. :23.000	Max. :5.000	Max. :99.00	Max. :30.000

Besides the responsible variable, there are 8 interesting variables,SLEPTIM1,GENHLTH, ALCDAY5, SEXVAR, X_RFSMOK3, X_AGEG5YR, EXERANY2, DRNKANY5. Figure 2 shows all four interesting numerical reasons that may affect the Body Mass Index. Panel A is called the "sleeping time for each respondent." It is generated by SLEPTIM1 and represents the total sleeping time every day for each respondent. The sleeping time is right-skewed and single-peaked which means almost all of Americans sleep under 10 hours From the table, I found the median of sleep time is 7 hours and mean is 7.1 which is a healthy duration since most adults need 7 to 9 hours or less. There is some extreme value on the right tail, which is over 20 hours. But considering there is some illnesses, such as Kleine-Levin Syndrome could cause this result(M. Poppe 2003), I did not filter them.
Panel B is called "the general self-rated health for each respondent." The data is calculated from GENHLTH and represents self-rated general health in 5 different grades. where 1 means "Excellent" and 5 means "poor." All respondents are required to answer the question, "Would you say that in general your health is?" The sleeping time is right-skewed and single-peaked as well. The median is 2 and the mean is 2.4, which means most of the citizens have an above Good feeling about their life. The major responses are concentrated in the score of 2 and 3, which is because the Americans may not be prone to give extremely worse emotional expressions when rating their feeling about life.
Panel C is the age of each respondent. Since the original data only provided 13 five-year age categories, X_AGEG5YR, I randomly assigned the age for each respondent in all 13 groups separately. In the plot, The shape is symmetric and single-peaked. The median is 57 years old and the mean is 55 years old. Panel D is the alcohol each respondent drinks every day and the variable name is ALCDAY5. All respondents must answer the question, "During the past 30 days, how many days did you have at least one drink of any alcoholic beverage?" The alcohol drinking is right-skewed and single-peaked and can be proved by the median on the table, which is only 1 and the mean is 3.882. So, most Americans do not drink at all.

Fig.3 Barplot of four categorical variables



The figure 3 above is the Barplot of four interesting categorical variables, from left to right is "drink alcohol or not," "Male or Female," "smoke or not," and "exercise or not." Each of them has 2 levels shown on the graph. For exercise and smoking, It is fairly apparent that most of the people exercise regularly and have no smoking habit. Other than that, about half of the population is male and about 170000 is abstinent.

Methodology

This study aims to find the most relevant variables with a linear relationship with Body Mass Index, so a linear regression model is applied. Linear regression is a statistical analysis method that uses regression analysis in mathematical statistics to determine the relationship between two or more variables: dependent variables and multiple other independent variables. Here, I have more than one variable, so the process is called multiple linear regression. Since the model parameters are unknown we could estimated from the data by using linear predictor functions. It is expressed extensively in the form of y = w'x + y'z+e, where e is a normal distribution with a mean of 0 and is ignorable.

The full model assumes that:

$$Y = \beta_0 + \beta_1 * SLEPTIM1 + \beta_2 * GENHLTH + \beta_3 * SEXVAR + \beta_4 * X_RFSMOK3 + \beta_5 * X_AGEG5YR$$
$$+\beta_6 * EXERANY2 + \beta_7 * DRNKANY5$$

where, Y : the response variable: Body Mass Index
β_0 = the interaction term where every independent variable is equal to 0
β_1 = the expected change of Y for an unit increase in sleeping time
β_2 = the expected change of Y for an unit increase in general health
β_3 = the expected change of Y for an unit increase in age
β_4 = the expected change of Y for the value of the sex
β_5 = the expected change of Y for the value of the smoking
β_6 = the expected change of Y for the value of the exercise
β_7 = the expected change of Y for the value of the drinking alcohol

There are seven variables of interest for my multiple linear regression model. In general, there are two types of linear regression models that can be plotted, one is several parallel straight lines and the other is straight lines with interaction. By looking at the equation only, it is impossible that the lines are parallel with each other since the β for different variables are different. However, since I have more than two independent variables, It is hard to draw a 2d graph. So instead, the conclusion will be shown in tables.
For the reason to fit the best predictive model to the observed data set and the values of Y, there are a few steps to mutate the model. The first step is data validation. I separated data into "train" and "test" 2 datasets. The target is to achieve a rationally similar performance as a result. The model should not only fit on this dataset we have collected, even though it is relevantly huge but also on others from the same population in America. Applying the multiple linear regression model on both datasets is the next step. To make sure the model is fitted, I use a residual plot for each of them could be applied to prove that there is no violation in linearity, constant variance, independence and normality. A residual plot is a commonly used diagnostic tool in multiple regression, especially to evaluate whether a model contains nonlinear terms in various dependent variables. If any of the violations above is satisfied, we need to adjust the model to eliminate it. Simultaneously, there are 2 conditions that have to be met in case the residual plot is trusted. The condition one is a clear pattern with the response value and fitted value and the other one is no clear pattern between each independent value which indicates no correlation. This could also be checked by function vif. After that, I will use the box-cox transformation on both responses variable and independent value to discover how to fix the model. The box-cox transformation is used to transform the data which is not normally distributed. It automatically computes the transformation powers into the best-fitted one. Furthermore, a model reduction is the next tool to compare different factors in the model and filter the insignificant ones. This is the best way to get rid of its dross and get its essence. There are three selection criteria: R^2adj, AIC and BIC. For any model,the largest R^2adj, smallest AIC and BIC for the model is the best subset of each size. Last but not least are removing insignificant variables and problematic observations. Leverage Point, Outlier and Cook's Distance are three kinds of data points that I will remove systematically. Leverage Points are points that have x-values with a tremendous effect on the estimated regression model. Cook's Distance is the y-values with a tremendous effect on the estimated regression model. Outliers are points that do not follow the pattern set of the data. The plot will be more clear to view after filtering them off.

Result

Model

The model was run on 7 independent variables to explore the relationship between all factors and BMI in two groups: training group and test group.

Train

Table3: box-cox transformation

Coefficients	Estimate	P value
Intercept	1.921e-01	<2e-16 ***
sleeping time	1.539e-03	<2e-16 ***
general health	-1.204e-02	<2e-16 ***
sex	6.356e-03	<2e-16 ***
smoke	-4.994e-03	<2e-16 ***
age	4.953e-05	<2e-16 ***
exercise	4.514e-03	<2e-16 ***
drinking alcohol	2.325e-03	<2e-16 **
Multiple R-squared: 0.06829, Adjusted R-squared: 0.06826		

I randomly select 80% responses of the total dataset to form the training dataset. After checking the residual plot, there is enough evidence that could indicate some of the assumptions are violated. So I apply the box-cox transformation to the training group. Table 3 is a general summary of the box-cox transformation. Since all the p-values are extremely small and smaller than 0.05, all of them should be significant and not rejected, but whether there is a causal relationship between them and BMI is not clear. Besides, the adjusted r-squared is relatively low, which means there is almost no trend, regardless of whether they are logically related. All in all, I combined it with the output of box-cox transformation, the following model is formed:

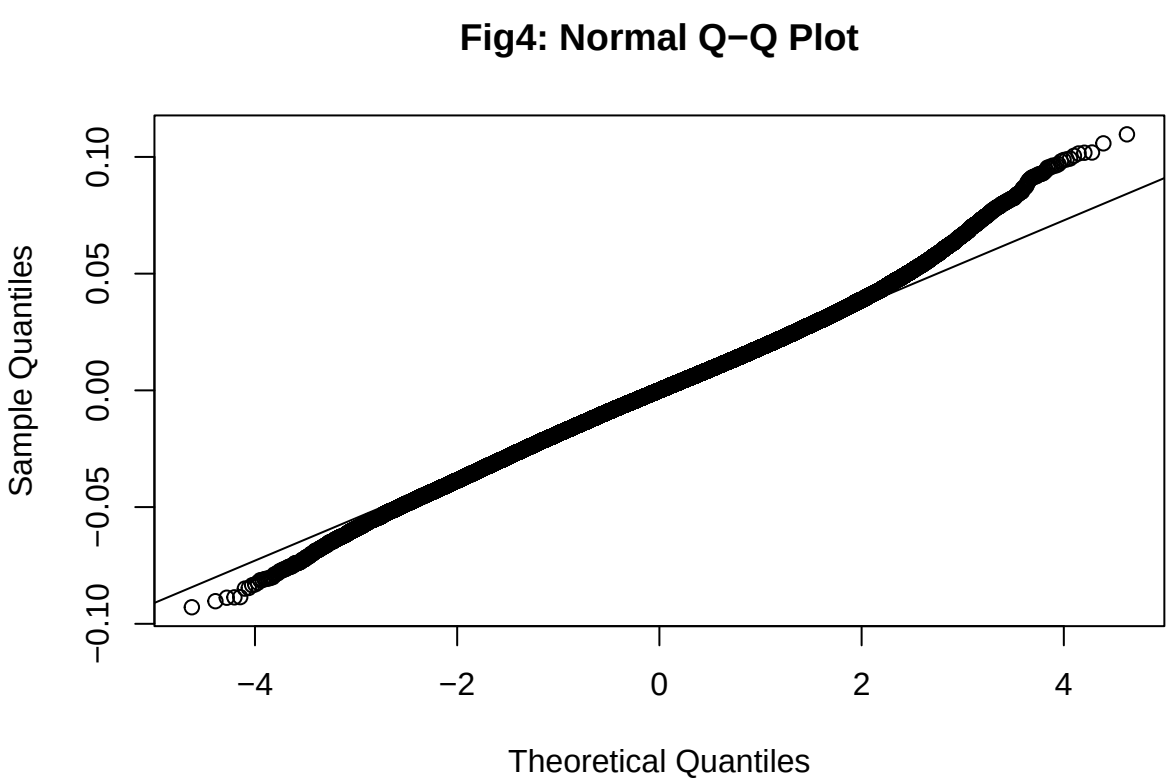
$$Y^{-0.5} = 1.921e^{-01} + 1.539e^{-03} * SLEPTIM1^{0.66} - 1.204e^{-02} * GENHLTH^{0.5} + 6.356e^{-03} * SEXVAR^{0.5}$$
$$-4.994e^{-03} * X_RFSMOK3^{-10} + 4.953e^{-05} * X_AGEG5YR 4.514e^{-03} * EXERANY2^{-6} + 2.325e^{-03} * DRNKANY5^{-0.5}$$

The box-cox transformation will give a suggested change on the power of each factor. In this case, The main effect of the sleeping time is $1.539e^{-03}$, the power of the sleeping time is 0.66 representing that the BMI increases by 0.0392, the root of $1.539e^{-03}$ since BMI has a power of 0.5 when I increase 1 unit in sleeping time.

Table4: Vif

sleeping time	general health	sex	smoke	age	exercise	drinking alcohol
1.025300	1.154639	1.015313	1.046565	1.089449	1.108380	1.064806

Next step, I check the vif in order to avoid multicollinearity. All of them are round than 1 which means not correlated.



In the methodology, There is an assumption that the error term (e) in the multiple linear regression model is under normal distribution, which also means the total model should also follow a normal distribution. Therefore here is the Normal Q-Q Plot, which indicates the normality is not violated if a strong linear pattern is closed to the diagonal. From this Normal Q-Q Plot, the points follow a strong linear pattern in the mid of the lines but shift away on both ends. Since the residual plot is also well formed, I would like to say that our data is normally distributed and the model is correct.

Table5: model reduction

model	adj R^2	AIC	BIC
Original	0.06826133	-1351736	-1351641
Reduction	0.06087429	-1349636	-1349552

In table 5, I tried to add a new factor called mental health instead of drinking alcohol and smoking since those two activities could be associated with psychological distress(Martin Paulus 2009) and I hope to get a reduced model. However, the reduced model has a lower adj R^2 as 0.060 and a bigger AIC and BIC, relevantly speaking. In this case, the original model is kept. Last but not least, there are 171 problematic observations in the data.

Test

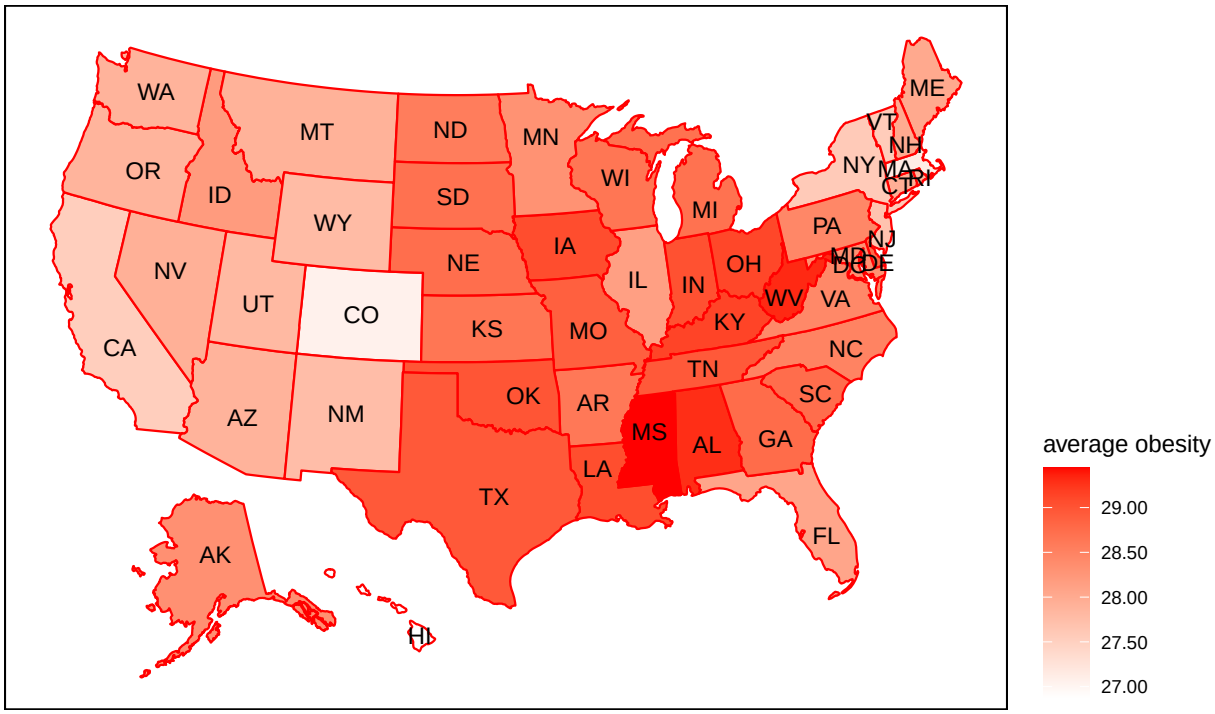
I form the test dataset the rest 20% responses of the total dataset and apply the same steps and transformation to it. The estimates are close to the training model as below and there is no violation on residual plot. In conclusion, the final model is valid.

Table6: box-cox transformation

Coefficients	Estimate	P value
Intercept	1.921e-01	<2e-16 ***
sleeping time	1.434e-03	<2e-16 ***
general health	-1.218e-02	<2e-16 ***
sex	6.096e-03	<2e-16 ***
smoke	-4.869e-03	<2e-16 ***
age	5.810e-05	<2e-16 ***
exercise	4.307e-03	<2e-16 ***
drinking alcohol	2.791e-03	1.05e-07 ***

Map

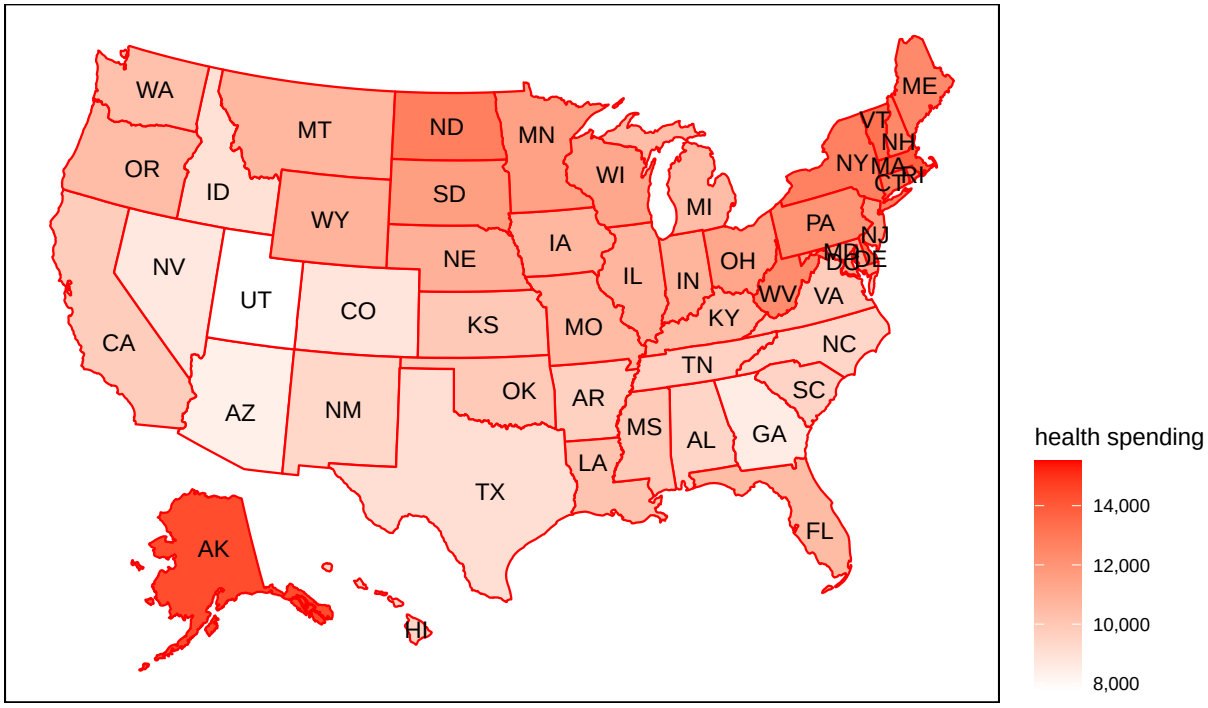
Fig.5: average obesity in each state



As we all know, there are plenty of other reasons and factors that I mentioned before that could apply to the BMI since it is a quite complicated and personal data. Figure 5 describes the state-by-state trends of BMI in the U.S. As shown in Figure 5, the overall body mass function in the United States is around 28 as mentioned in data section. As the codebook of the dataset describe, if the BMI of one person is between 25 and 30 then the he is overweighted. So the average BMI of all states are not healthy. Moreover, except for the average 26 BMI in Colorado, all the other states have at least 27 BMI. Among them, the overall BMI in the western states of the United States was smaller, with WA,OR, ID, CA, NV, UT, CO, AZ, NM, MT and WY with an average around 27.5. On the other hand, the middle and eastern states saw a greater BMI average around 28.5 where Mississippi has BMI over 29.4.

Since overweight could be a serious problem for every state, the government does put a lot of its Budget on it. The second map, fig.6 shows the health spending per capita in each states. As shown in Figure 6, the health spending per capita in the United States is around 10k,where Utah has lowest one about 7776.6 dollar per capita, and D.C has the highest one as 15527.2 dollar per capita. However, the health spending per capita is related to the total government spending and it is different in each state, so the result is not accurate.

Fig.6: health spending per capita in each states



Discussion

Numerous observations have illustrated that all seven factors affect BMI from the results. By using multiple linear regression, drinking alcohol, being female, not smoking, and exercising are four categorical factors that increase BMI for respondents in America. It seems quite strange that exercise increases BMI, however, increased muscle does also add a little weight since more glycogen will be stored in your body. Additionally, in numerical summary, the more time a person sleeps, the higher his BMI. Age also affects BMI. As people get older, their BMI will rise as well. Being overweight will cause other general health problems, such as meningioma(Brown WV 2009), so that it has an inverse relationship with general health. From the first map, we learn that geographical location also affects BMI. The West coast has a lower BMI than the East coast. There are various reasons for this result, such as the east coast cohorts have higher Persistent organic pollutant exposure levels as compared to the west coast cohorts(Rylander et al. 2012). In this case, splitting the map in two and reanalyzing it later is the best option. Combining the two maps in the result, we can conclude that health spending per capita could reduce the BMI in some ways. On the west coast, the average BMI is low with lower health spending. Other than that, the states in the east-north of America invest more in citizens' personal health. This causes their BMI to be lower than all the states around them.

Weakness

From the methodology, I have already generated 171 problematic observations from Leverage Point, Outlier and Cook's Distance in the data. However, the original data has 200000 observations, and 171 is an extremely small minority, relatively speaking. Therefore, for the reason of integrity and authenticity of the data, I kept all of them, which may cause some offset in the model. When generating the new variable, "Age," the random sampling is applied, which will cause some limitations on the actual age of the respondent. Last but not least, respondents could intentionally modify the weight and height will also cause some problems on accuracy.

Future work

In order to make the report better and the research data more accurate and comprehensive, searching and collecting more data by methods other than the survey is necessary. For example, measuring the height and weight rather than survey will reduce bias. I hope to look into the exercise type of each respondent and a real age for each respondent in order to fit a better model. A table with a percentage of the health spending in the total government spending would be more accurate data than only health spending.

Appendix

The numbering of 171 problematic observations in the data.

```
##   1428   1565   2265   4246   5279   6588   7131   7649   8003   8095   8725
##   1428   1565   2265   4246   5279   6588   7131   7649   8003   8095   8725
##   8975   9255   9334   9668   9897  10754  13143  16354  16375  17463  17917
##   8975   9255   9334   9668   9897  10754  13143  16354  16375  17463  17917
##  18132  21849  22376  24770  24899  25049  30033  31659  31753  32474  33202
##  18132  21849  22376  24770  24899  25049  30033  31659  31753  32474  33202
##  33824  34027  35034  38864  41067  41855  42348  42951  43600  47117  49781
##  33824  34027  35034  38864  41067  41855  42348  42951  43600  47117  49781
##  51738  52558  54128  55945  56802  57902  60685  61214  61326  62424  63371
##  51738  52558  54128  55945  56802  57902  60685  61214  61326  62424  63371
##  64182  67546  67955  74439  74480  78771  79472  80724  81606  82144  82234
##  64182  67546  67955  74439  74480  78771  79472  80724  81606  82144  82234
##  83257  83274  83774  87724  88142  88200  89118  91687  92733  93419  94427
##  83257  83274  83774  87724  88142  88200  89118  91687  92733  93419  94427
##  95217  97575 102736 105440 105642 107173 109200 109362 111683 113375 121389
##  95217  97575 102736 105440 105642 107173 109200 109362 111683 113375 121389
## 123077 125031 128894 129918 130174 130585 131867 136866 141106 147049 147853
## 123077 125031 128894 129918 130174 130585 131867 136866 141106 147049 147853
## 151987 152032 157687 158667 160172 166238 167230 167501 168574 170399 170801
## 151987 152032 157687 158667 160172 166238 167230 167501 168574 170399 170801
## 170939 170999 171338 171392 172986 174434 174497 181353 183442 187678 188873
## 170939 170999 171338 171392 172986 174434 174497 181353 183442 187678 188873
## 189066 190404 191898 192945 193061 193127 193698 196559 196729 198229 198405
## 189066 190404 191898 192945 193061 193127 193698 196559 196729 198229 198405
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## 198506 202586 204289 204327 204341 207659 209477 210764 212551 214014 214287
## 217548 217582 219021 220924 222816 222845 222994 223285 224386 224806 226953
## 217548 217582 219021 220924 222816 222845 222994 223285 224386 224806 226953
## 228642 232352 234588 234795 235386 239180 239585 241723 242009 243621 243896
## 228642 232352 234588 234795 235386 239180 239585 241723 242009 243621 243896
## 244823 248670 251413 251537 259022 260590
## 244823 248670 251413 251537 259022 260590
```
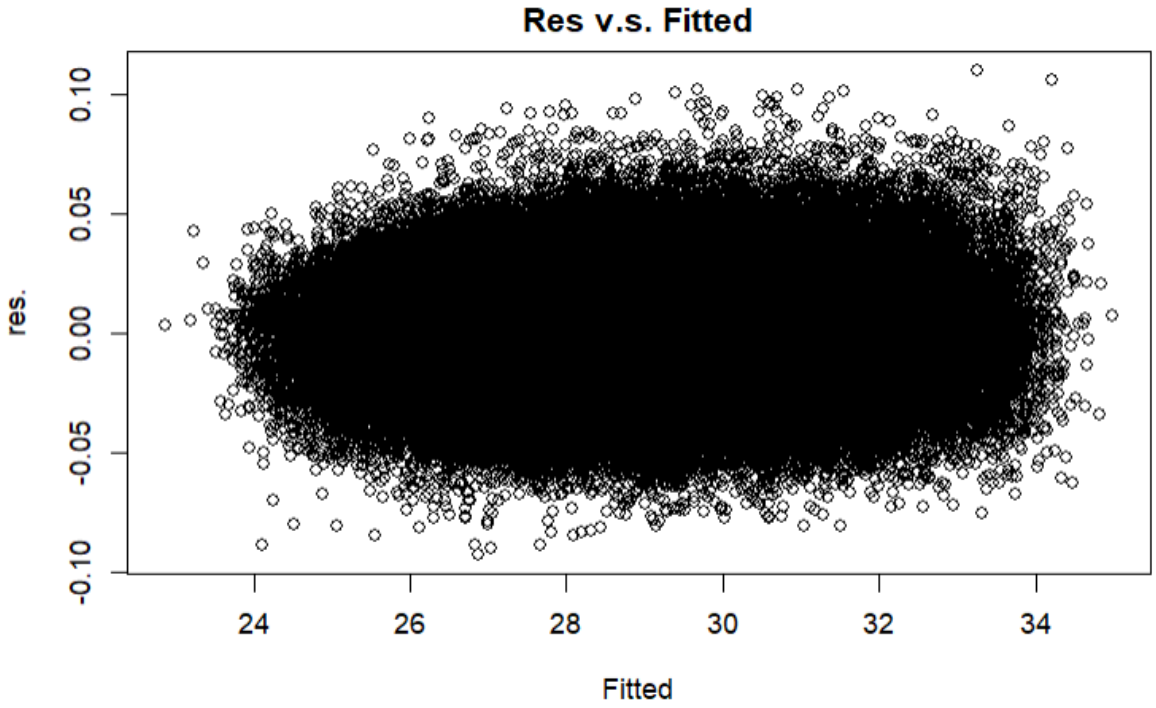

The residual plot after box-cox transform is showed below. This means the final model does not violate and assumption since the points are randomly assigned on both sides of res = 0.



Simulation

Since America current has 330 million population, I will run the Simulation 3300000 times.

Table 7: summary statistic of Body Mass Index

state_code	BMI	sleeping	health	sex	smoke	age	exercise	alcohol
11	62.08982	14	1	1	0	25	1	1
29	58.48451	15	4	1	1	93	1	1
32	72.96860	1	1	0	1	43	1	1
20	170.22612	0	3	1	1	79	0	0
40	54.97532	0	4	0	0	28	1	0
32	59.46997	8	3	0	0	79	1	1

For state code it is followed FIPS code. The BMI is selected from the lowest BMI ever 18.5 to highest one:186. The self rated health use the same criterion as the original survey and we know that everyday has 24 hours so sleeping time is between 0 to 24. This is strange but there does have some people is ill and need that much of sleeping time or does not need sleep at all. For sex 0 is male 1 female, smoke, exercise and alcohol 0 means does not do that and 1 means does. There is no transgender since it is not appeared in the original data.

Enhancements

Motivation

1. For what purpose was the dataset created?
   The dataset was created to identify variations in health-related behaviors in america

2. Who created this dataset?
   The Behavioral Risk Factor Surveillance System (BRFSS) and the Centers for Disease Control and Prevention (CDC).

3. What support was needed to make this dataset?
   CDC's Population Health Surveillance Branch, under the Division of Population Health at CDC's National Center for Chronic Disease Prevention and Health Promotion.

4. Any other comments? No.

Composition

1.What do the instances that comprise the dataset represent (for example, documents, photos, people, countries)? Are there multiple types of instances (for example, movies, users, and ratings; people and interactions between them; nodes and edges)?
This data set was recorded in American only.
2 How many instances are there in total?
401958
3.Does the dataset contain all possible instances or is it a sample (not necessarily random) of instances from a larger set? If the dataset is a sample, then what is the larger set? Is the sample representative of the larger set (for example, geographic coverage)? If so, please describe how this representativeness was validated/verified. If it is not representative of the larger set, please describe why not (for example, to cover a more diverse range of instances, because instances were withheld or unavailable). All individuals over 18 years old who is living America.
4.What data does each instance consist of? "Raw" data (for example, unprocessed text or images) or features? In either case, please provide a description.
Each instance consists general and health status of all individuals.
5.Is there a label or target associated with each instance? If so, please provide a description.
No.
6.Is any information missing from individual instances? If so, please provide a description, explaining why this information is missing (for example, because it was unavailable). This does not include intentionally removed information, but might include, for example, redacted text.
No
7.Are relationships between individual instances made explicit (for example, users' movie ratings, social network links)? If so, please describe how these relationships are made explicit.
No.
8.Are there recommended data splits (for example, training, development/validation, testing)? If so, please provide a description of these splits, explaining the rationale behind them.
Yes. total samples in data is 401958.Valid samples in data is 332479.test dataset is 66496(20%). Train dataset is265983(80%).
9.Are there any errors, sources of noise, or redundancies in the dataset? If so, please provide a description.
Yes, some individuals does not response all questions.
10.Is the dataset self-contained, or does it link to or otherwise rely on external resources (for example, websites, tweets, other datasets)? If it links to or relies on external resources, a) are there guarantees that they will exist, and remain constant, over time; b) are there official archival versions of the complete dataset (that is, including the external resources as they existed at the time the dataset was created); c) are there

any restrictions (for example, licenses, fees) associated with any of the external resources that might apply to a dataset consumer? Please provide descriptions of all external resources and any restrictions associated with them, as well as links or other access points, as appropriate.
Self-contained.
11.Does the dataset contain data that might be considered confidential (for example, data that is protected by legal privilege or by doctor-patient confidentiality, data that includes the content of individuals' non-public communications)? If so, please provide a description.
No.
12.Does the dataset contain data that, if viewed directly, might be offensive, insulting, threatening, or might otherwise cause anxiety? If so, please describe why.
No.
13.Does the dataset identify any sub-populations (for example, by age, gender)? If so, please describe how these subpopulations are identified and provide a description of their respective distributions within the dataset.
Yes, age group and gender.
14.Is it possible to identify individuals (that is, one or more natural persons), either directly or indirectly (that is, in combination with other data) from the dataset? If so, please describe how.
No.
15.Does the dataset contain data that might be considered sensitive in any way (for example, data that reveals race or ethnic origins, sexual orientations, religious beliefs, political opinions or union memberships, or locations; financial or health data; biometric or genetic data; forms of government identification, such as social security numbers; criminal history)? If so, please provide a description.
No.
16.Any other comments?
No.

Collection process

1.How was the data associated with each instance acquired? Was the data directly observable (for example, raw text, movie ratings), reported by subjects (for example, survey responses), or indirectly inferred/derived from other data (for example, part-of-speech tags, model-based guesses for age or language)? If the data was reported by subjects or indirectly inferred/derived from other data, was the data validated/verified? If so, please describe how.
The data were gathered from the The Behavioral Risk Factor Surveillance System (BRFSS).
2.What mechanisms or procedures were used to collect the data (for example, hardware apparatuses or sensors, manual human curation, software programs, software APIs)? How were these mechanisms or procedures validated? By phone call.
3.If the dataset is a sample from a larger set, what was the sampling strategy (for example, deterministic, probabilistic with specific sampling probabilities)?
The dataset is not a sample.
4.Who was involved in the data collection process (for example, students, crowdworkers, contractors) and how were they compensated (for example, how much were crowdworkers paid)?
BRFSS.
5.Over what timeframe was the data collected? Does this timeframe match the creation timeframe of the data associated with the instances (for example, recent crawl of old news articles)? If not, please describe the timeframe in which the data associated with the instances was created.
In 2020.
6.Were any ethical review processes conducted (for example, by an institutional review board)? If so, please provide a description of these review processes, including the outcomes, as well as a link or other access point to any supporting documentation.
No.
7.Were the individuals in question notified about the data collection? If so, please describe (or show with

screenshots or other information) how notice was provided, and provide a link or other access point to, or otherwise reproduce, the exact language of the notification itself.
yes, they answered phone call.
8.Did the individuals in question consent to the collection and use of their data? If so, please describe (or show with screenshots or other information) how consent was requested and provided, and provide a link or other access point to, or otherwise reproduce, the exact language to which the individuals consented. yes, they answered phone call.
9.If consent was obtained, were the consenting individuals provided with a mechanism to revoke their consent in the future or for certain uses? If so, please provide a description, as well as a link or other access point to the mechanism (if appropriate). No. 10.Has an analysis of the potential impact of the dataset and its use on data subjects (for example, a data protection impact analysis) been conducted? If so, please provide a description of this analysis, including the outcomes, as well as a link or other access point to any supporting documentation. No. 11.Any other comments? No.

Preprocessing/cleaning/labeling

1.Was any preprocessing/cleaning/labeling of the data done (for example, discretization or bucketing, tokenization, part-of-speech tagging, SIFT feature extraction, removal of instances, processing of missing values)? If so, please provide a description. If not, you may skip the remaining questions in this section.
Yes cleaning of the data was done.
2.Was the "raw" data saved in addition to the preprocessed/cleaned/labeled data (for example, to support unanticipated future uses)? If so, please provide a link or other access point to the "raw" data.
No.
3.Is the software that was used to preprocess/clean/label the data available? If so, please provide a link or other access point. R was used.
4.Any other comments?
No

Uses

1.Has the dataset been used for any tasks already? If so, please provide a description.
Yes, CDC own report. (https://www.cdc.gov/brfss/annual_data/2020/pdf/2020-sdqr-508.pdf)/ 2.Is there a repository that links to any or all papers or systems that use the dataset? If so, please provide a link or other access point. No 3.What (other) tasks could the dataset be used for? Heart disease. 4.Is there anything about the composition of the dataset or the way it was collected and preprocessed/cleaned/labeled that might impact future uses? For example, is there anything that a dataset consumer might need to know to avoid uses that could result in unfair treatment of individuals or groups (for example, stereotyping, quality of service issues) or other risks or harms (for example, legal risks, financial harms)? If so, please provide a description. Is there anything a dataset consumer could do to mitigate these risks or harms? No. 5.Are there tasks for which the dataset should not be used? If so, please provide a description. No. 6.Any other comments? No.

Distribution

1.Will the dataset be distributed to third parties outside of the entity (for example, company, institution, organization) on behalf of which the dataset was created? If so, please provide a description.
GitHub.
2.How will the dataset be distributed (for example, tarball on website, API, GitHub)? Does the dataset have a digital object identifier (DOI)?
GitHub.

3.When will the dataset be distributed?
The dataset is available now.
4.Will the dataset be distributed under a copyright or other intellectual property (IP) license, and/or under applicable terms of use (ToU)? If so, please describe this license and/ or ToU, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms or ToU, as well as any fees associated with these restrictions.
No.
5.Have any third parties imposed IP-based or other restrictions on the data associated with the instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any relevant licensing terms, as well as any fees associated with these restrictions.
No.
6.Do any export controls or other regulatory restrictions apply to the dataset or to individual instances? If so, please describe these restrictions, and provide a link or other access point to, or otherwise reproduce, any supporting documentation.
No.
7.Any other comments?
No.

Maintenance

1.Who will be supporting/hosting/maintaining the dataset?
BRFSS
2.How can the owner/curator/manager of the dataset be contacted (for example, email address)?
subscriptions @ cdc.gov
3.Is there an erratum? If so, please provide a link or other access point.
No.
4.Will the dataset be updated (for example, to correct labeling errors, add new instances, delete instances)? If so, please describe how often, by whom, and how updates will be communicated to dataset consumers (for example, mailing list, GitHub)?
No.
5.If the dataset relates to people, are there applicable limits on the retention of the data associated with the instances (for example, were the individuals in question told that their data would be retained for a fixed period of time and then deleted)? If so, please describe these limits and explain how they will be enforced.
No.
6.Will older versions of the dataset continue to be supported/hosted/maintained? If so, please describe how. If not, please describe how its obsolescence will be communicated to dataset consumers.
No.
7.If others want to extend/augment/build on/contribute to the dataset, is there a mechanism for them to do so? If so, please provide a description. Will these contributions be validated/verified? If so, please describe how. If not, why not? Is there a process for communicating/distributing these contributions to dataset consumers? If so, please provide a description.
No.
8.Any other comments?
No.

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