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HS 616
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Data Simulation Project Write-Up

Adolescent obesity is quickly becoming a major public health problem in the United States. Increasingly sedentary lifestyles and easy access to processed, unhealthy foods have been tagged as major contributors to recent rises in obesity among adolescents. There has also been a great deal of research into other possible contributing factors. Gordon-Larsen et al. (2003) posited that these could include parental education, race, and other socioeconomic factors such as family income. Through their research the group found that 'family income and parental education had a limited effect on the disparities in overweight prevalence."

My data simulation aimed to emulate the distributions of sex, race, and income-level outlined in the research article and analyze some of the same relationships as the researchers. This included:

- % Overweight by Race
  - Stratified by sex
- % Overweight by Income Level
  - Stratified by race
- % Overweight by Parental Education
  - Stratified by race

My simulation began with the following table from the research article. The code below was used to create a sample of 10,000 adolescents with the appropriate proportions of each race, income level, and education level as seen in the table. The values in parentheses represent the proportion of the adolescents in that race each level of education and income.

Characteristic	Whites	African Americans	Hispanics	Asians
Parental education				
<HS	595 (8.96)	363 (17.66)	925 (41.90)	102 (17.29)
HS/GED	2253 (32.52)	787 (35.19)	566 (24.76)	172 (19.60)
Some College	2072 (29.20)	736 (24.51)	412 (17.70)	185 (17.00)
College Grad/Professional	1904 (25.30)	797 (18.65)	272 (11.59)	421 (41.07)
Family Income				
Mean Income	47,825	27,685	30,579	45,461
$0 to $20K	1067 (16.39)	1019 (46.39)	813 (38.17)	113 (15.41)
$20K to $40K	2213 (30.50)	938 (33.73)	924 (39.51)	352 (40.05)
$40K to $60K	2067 (28.94)	477 (11.63)	337 (13.78)	241 (23.72)
$60K to $80K	982 (13.79)	219 (5.32)	119 (5.02)	111 (10.24)
$80K+	806 (10.37)	142 (2.93)	70 (3.52)	103 (10.58)

<HS, no or some high school; HS/GED, high school/GED diploma.

```
# Create column of randomly selected race with probabilities based on the percentages in my research article

race <- c('white',sample(c('white','black','hispanic','asian'),size = 9999, replace = TRUE, prob =
c(.5441,.2131,.1726,.0702)))
data<- data.frame(race)

# Create column of parental education with probabilities based on the percentages from my research article
parental_education_white <- sample(c('<HS','HS/GED','Some College','College
Grad/Professional'),size=(length(data[which(data$race=="white"),])),replace = TRUE,prob =
c(.0896,.3252,.2920,.2530))

parental_education_black <- sample(c('<HS','HS/GED','Some College','College
Grad/Professional'),size=(length(data[which(data$race=="black"),])),replace = TRUE,prob =
c(.1766,.3519,.2451,.1865))

parental_education_hispanic <- sample(c('<HS','HS/GED','Some College','College
Grad/Professional'),size=(length(data[which(data$race=="hispanic"),])),replace = TRUE,prob =
c(.4190,.2476,.1770,.1159))

parental_education_asian <- sample(c('<HS','HS/GED','Some College','College
Grad/Professional'),size=(length(data[which(data$race=="asian"),])),replace = TRUE,prob =
c(.1729,.1960,.17,.4107))

# Add column to data frame
data$education[which(data$race =='white')] <- parental_education_white
data$education[which(data$race =='black')] <- parental_education_black
data$education[which(data$race =='hispanic')] <- parental_education_hispanic
data$education[which(data$race =='asian')] <- parental_education_asian
data$education <- as.factor(data$education)

# Create column of incomes for each race with probabilities based on the percentages from my research
article
income_level_white <- sample(c('$0-$20K','$20K-$40K','$40K-$60K','$60K-
$80K','$80K+'),size=(nrow(data[which(data$race=="white"),])),replace = TRUE,prob =
c(.1639,.3050,.2894,.1379,.1037))

income_level_black <- sample(c('$0-$20K','$20K-$40K','$40K-$60K','$60K-
$80K','$80K+'),size=(nrow(data[which(data$race=="black"),])),replace = TRUE,prob =
c(.4639,.3373,.1163,.0532,.0293))

income_level_hispanic <- sample(c('$0-20K','$20K-$40K','$40K-$60K','$60K-
$80K','$80K+'),size=(nrow(data[which(data$race=="hispanic"),])),replace = TRUE,prob =
c(.3817,.3951,.1378,.0502,.0352))

income_level_asian <- sample(c('$0-$20K','$20K-$40K','$40K-$60K','$60K-
$80K','$80K+'),size=(nrow(data[which(data$race=="asian"),])),replace = TRUE,prob =
c(.1541,.4005,.2372,.1024,.1058))

# Add column to data frame
data$income.level[which(data$race =='white')] <- income_level_white
data$income.level[which(data$race =='black')] <- income_level_black
data$income.level[which(data$race =='hispanic')] <- income_level_hispanic
data$income.level[which(data$race =='asian')] <- income_level_asian
data$income.level <- as.factor(data$income.level)
```

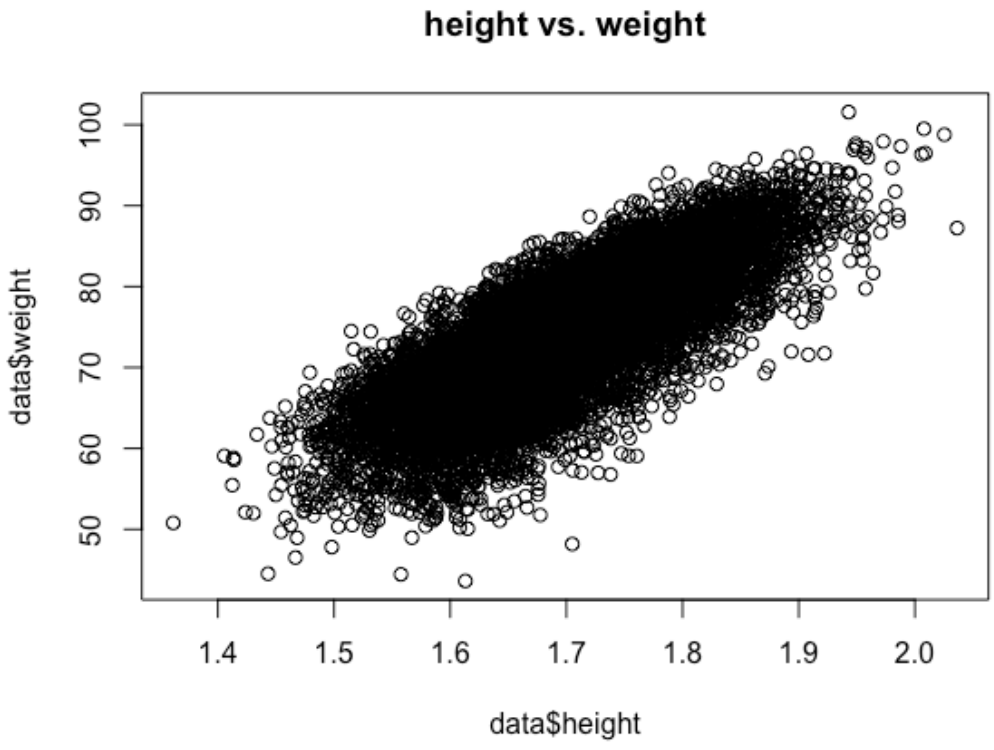
```
# Create column for sex with probabilities based on the percentages from my research article
data$sex <- c('male',sample(c('male','female'),size=(nrow(data)-1),replace = TRUE,prob = c(.535,.465)))
data$sex <- as.factor(data$sex)
```

The next step in simulating the data was creating height and weight values for each row. I retrieved the means and standard deviations for height and weight for men and women at 16 years old (as this was the mean age of the population in the article) from CDC census data.[1] Using this data I calculated the mean BMI for the two groups (mean weight/mean height^2). Height and weight are correlated variables so I used the following code to create a column of heights and then a column of weights for each sex.

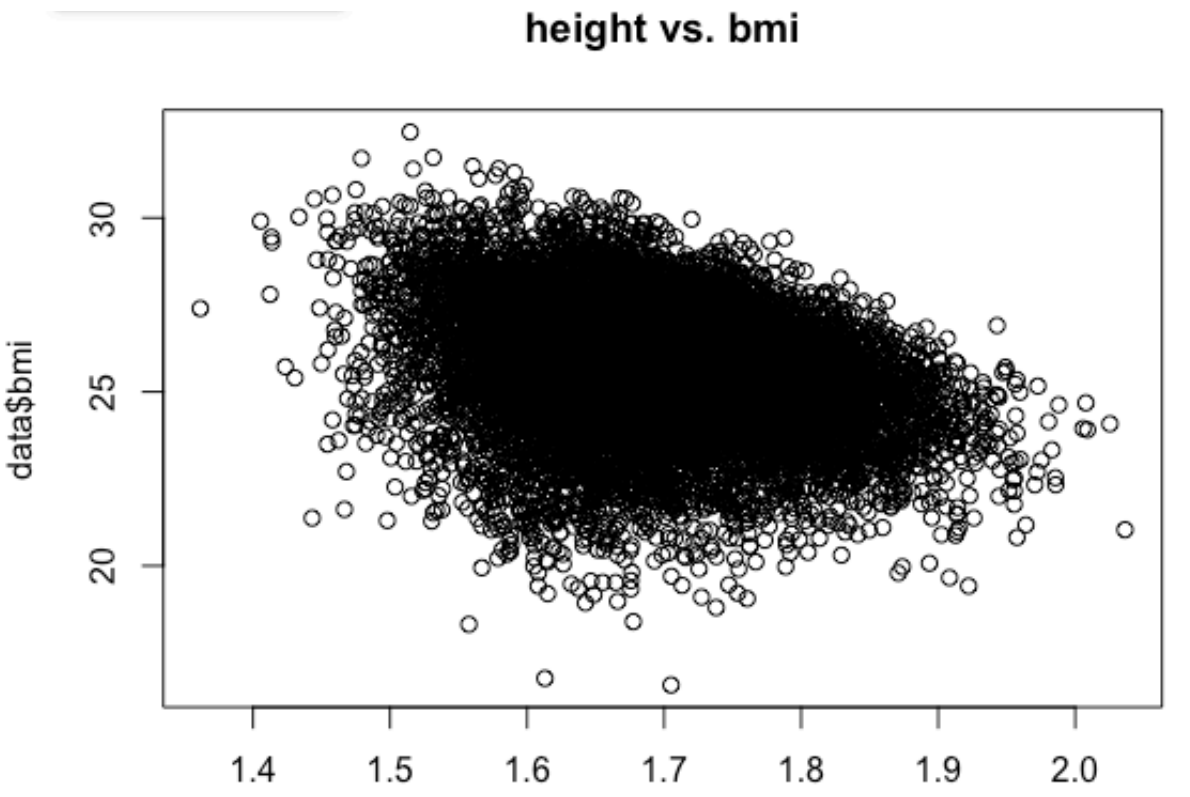
```
male_heights <- rnorm(male_n, mean=male_height_mean, sd=male_height_sd)
male_weights <- .6 * mean_male_bmi * (male_heights^2) + .4* (male_weight_mean + rsnorm(male_n,
sd=male_weight_sd,xi=-1.5))
```

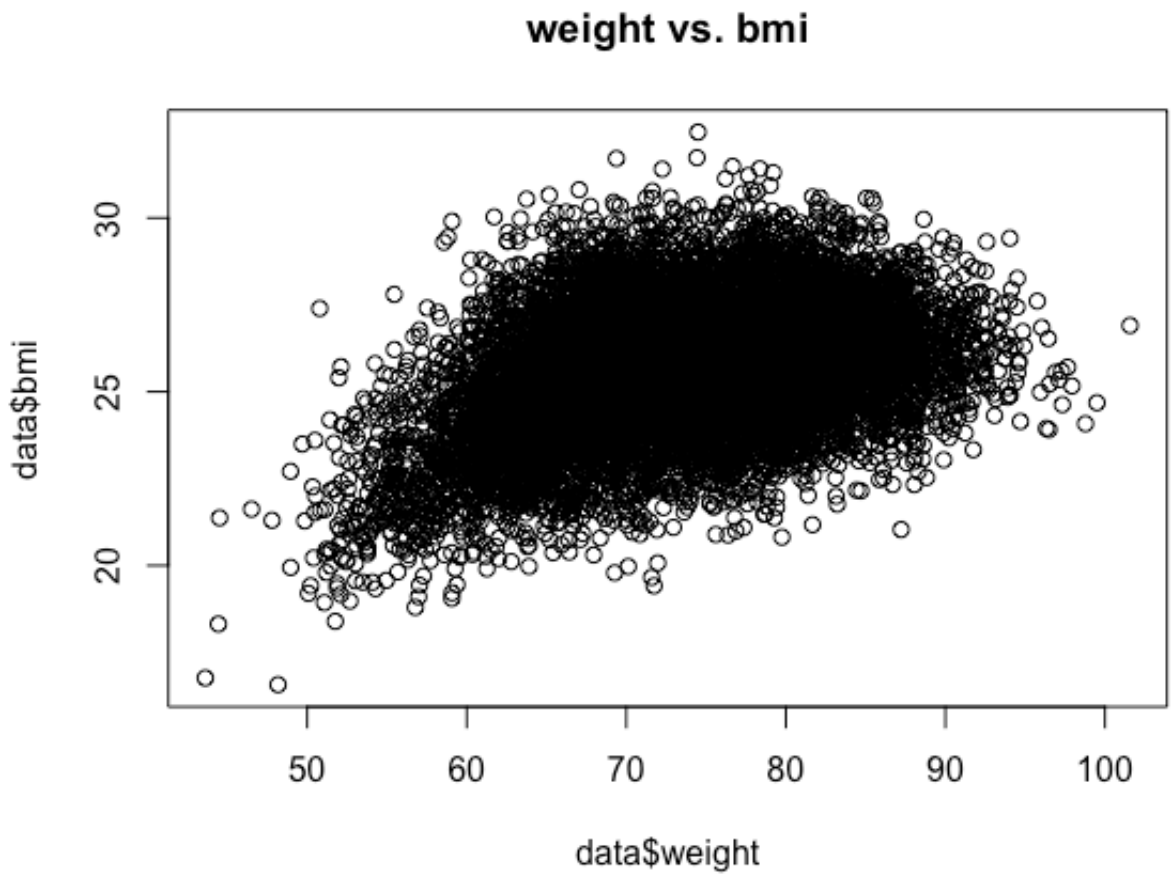
BMI was then calculated using the formula described above and added as a column to the data frame. Based on that column an "obese" column was created with 0 = not obese (BMI < 25) and 1 = obese (BMI >= 25). To ensure that the data was properly created the following plots were created to see the relationships between height and weight, height and BMI, and weight and BMI.

Height, Weight, BMI Scatter Plots



[1] https://www.cdc.gov/growthcharts/data/set1clinical/cj41l021.pdf and https://www.cdc.gov/growthcharts/data/set1clinical/cj41l022.pdf

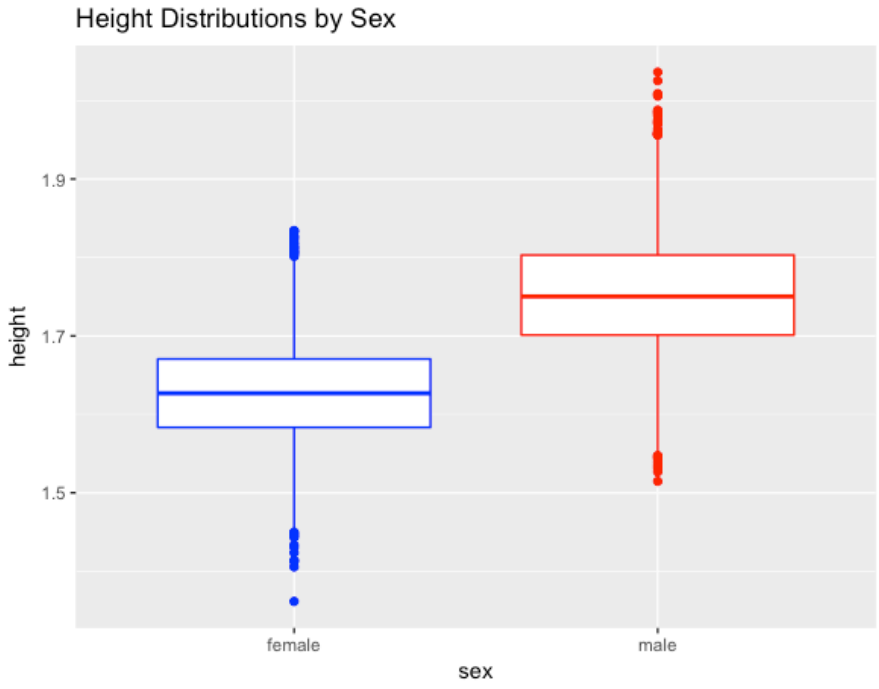

height vs. bmi
data$bmi
20
25
30
1.4
1.5
1.6
1.7
1.8
1.9
2.0

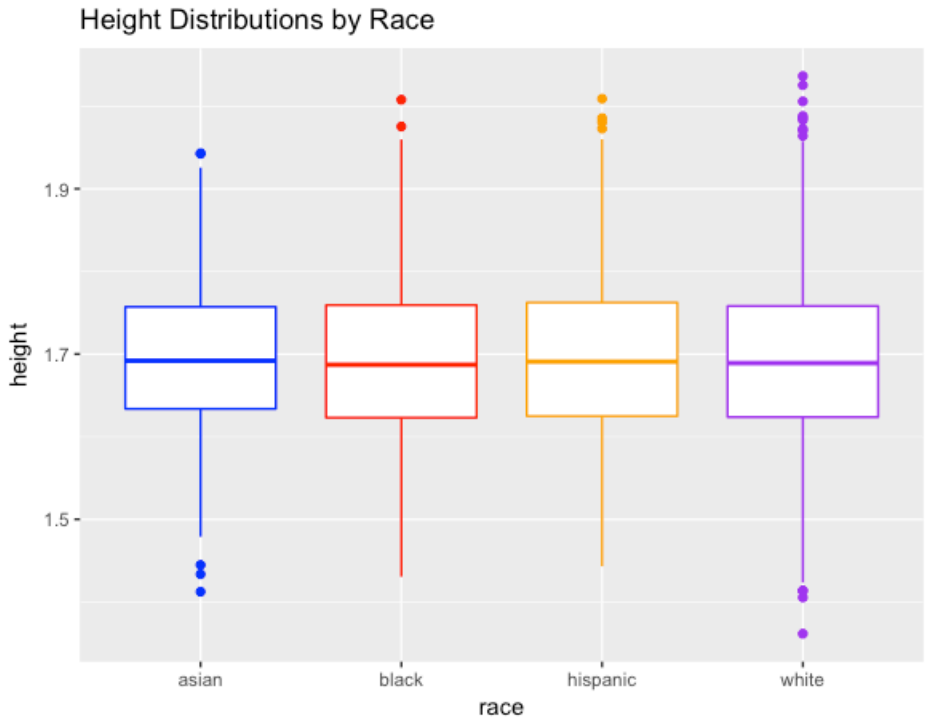

weight vs. bmi
data$bmi
20
25
30
50
60
70
80
90
100
data$weight

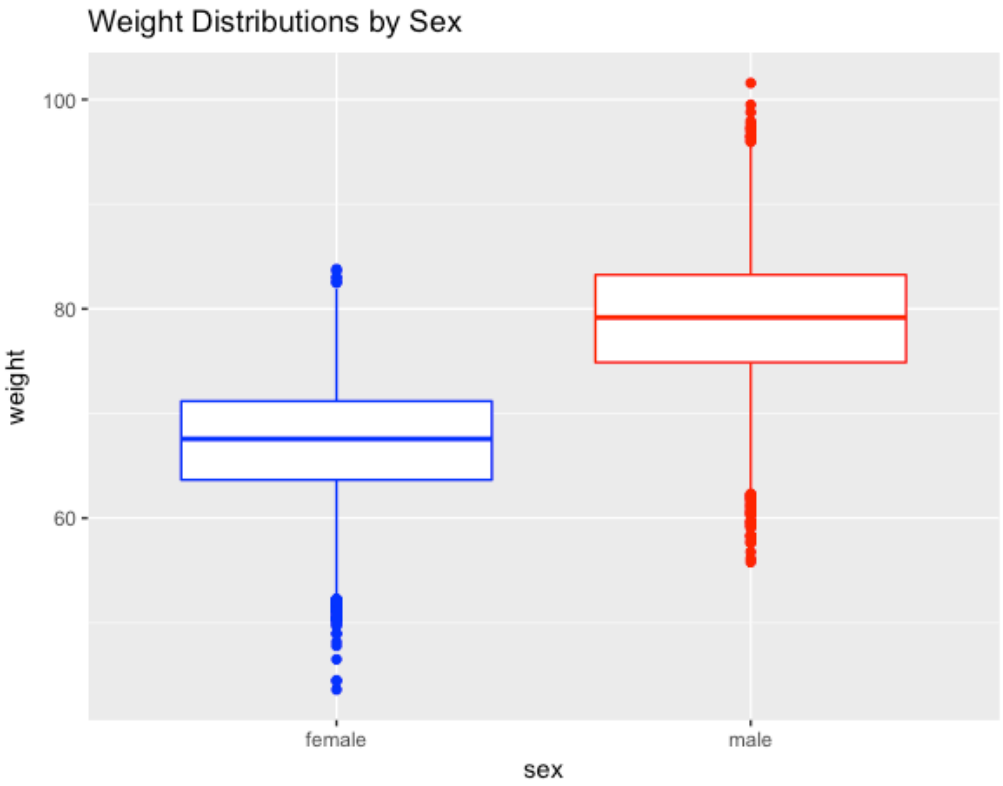
Based on the plots it was clear to see that the correlated variables had been created successfully. Higher heights correlated with higher weights and higher weights somewhat correlated with higher BMIs.

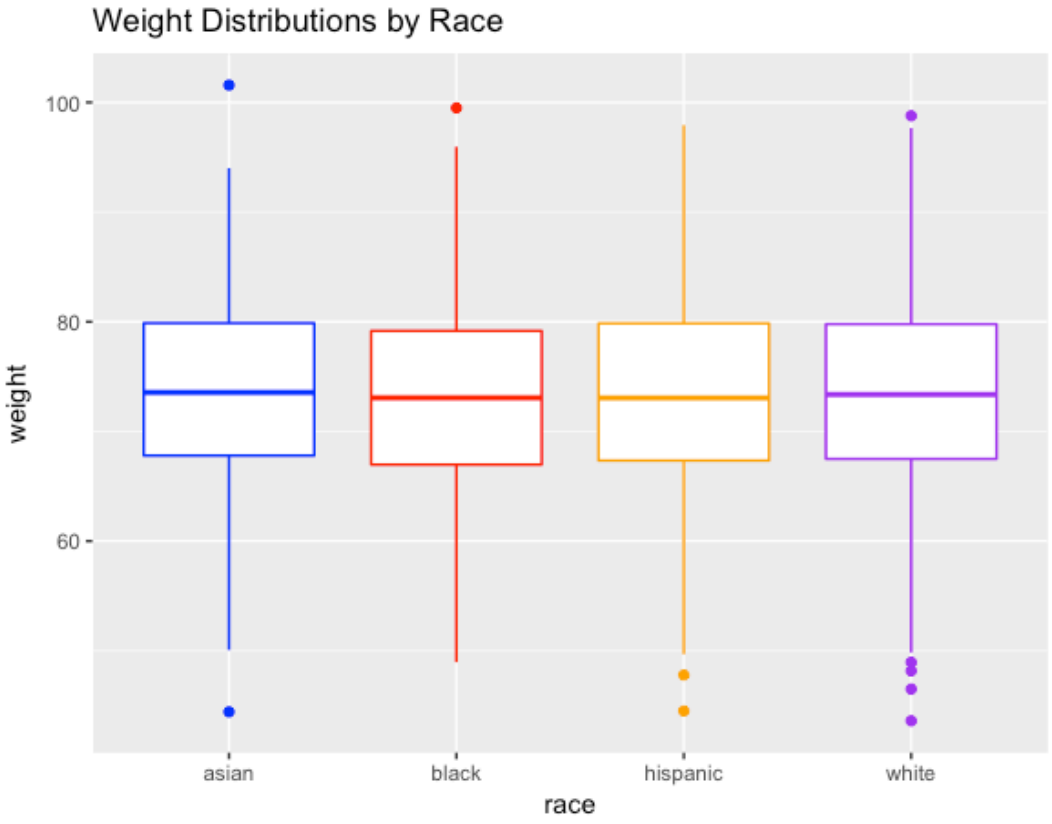
Next I wanted to see what the distributions for height, weight and BMI looked like across sex, race, and income level. The following plots display this information:

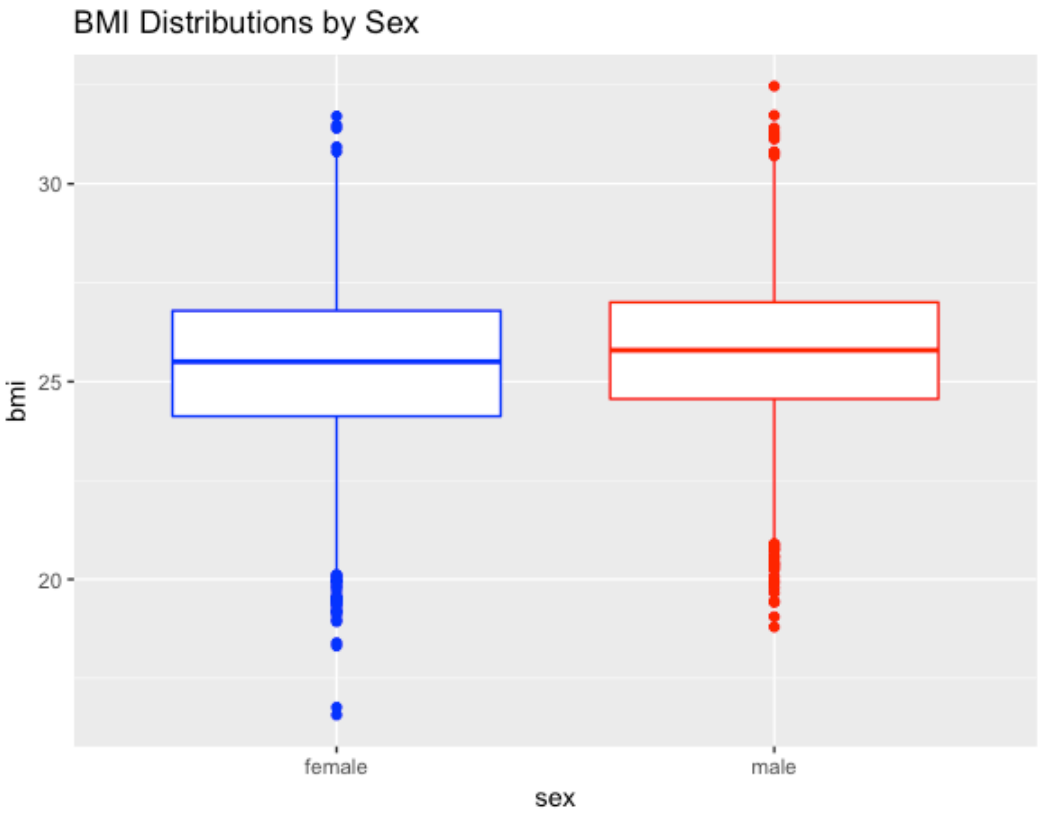
Population Characteristics Distributions

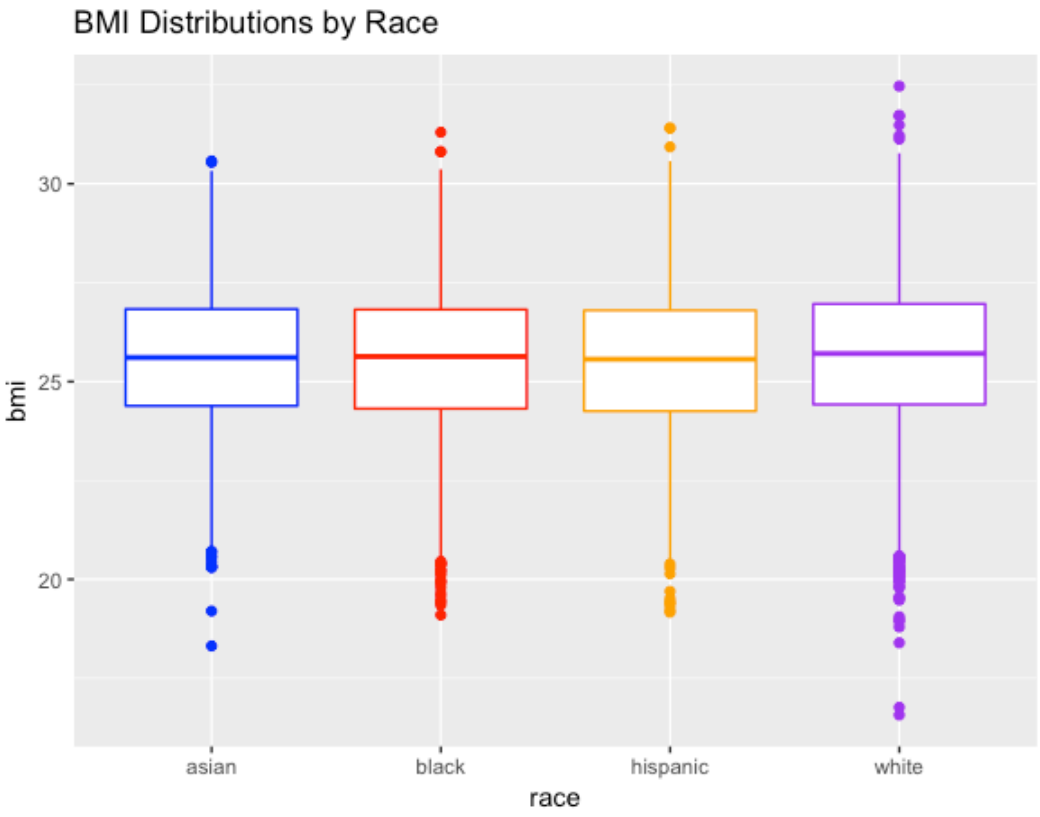


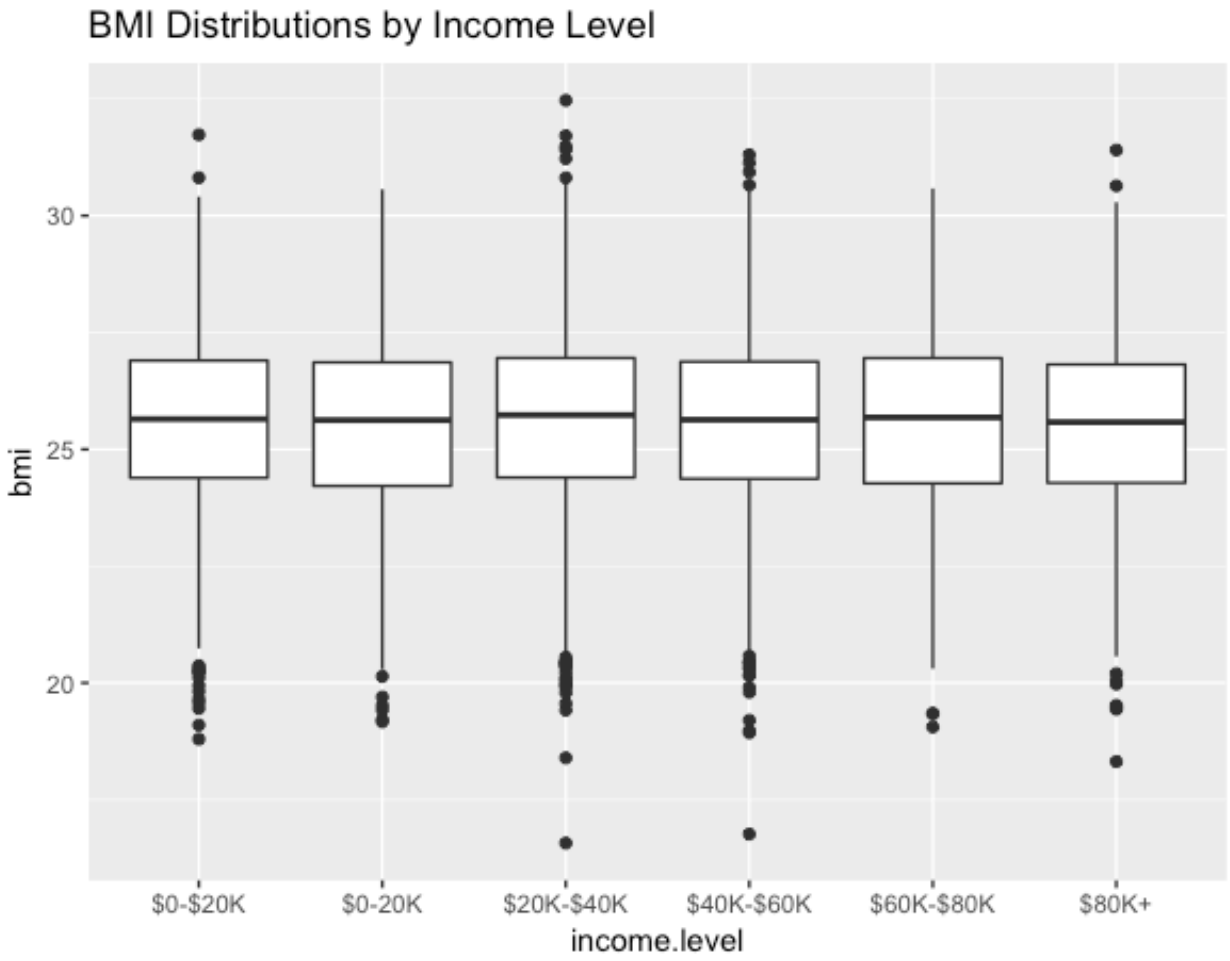



Weight Distributions by Sex
100
80
60
weight
female
male
sex


Weight Distributions by Race
100
80
60
weight
asian
black
hispanic
white
race


BMI Distributions by Sex
bmi
30
25
20
female
male
sex


BMI Distributions by Race
bmi
30
25
20
asian
black
hispanic
white
race

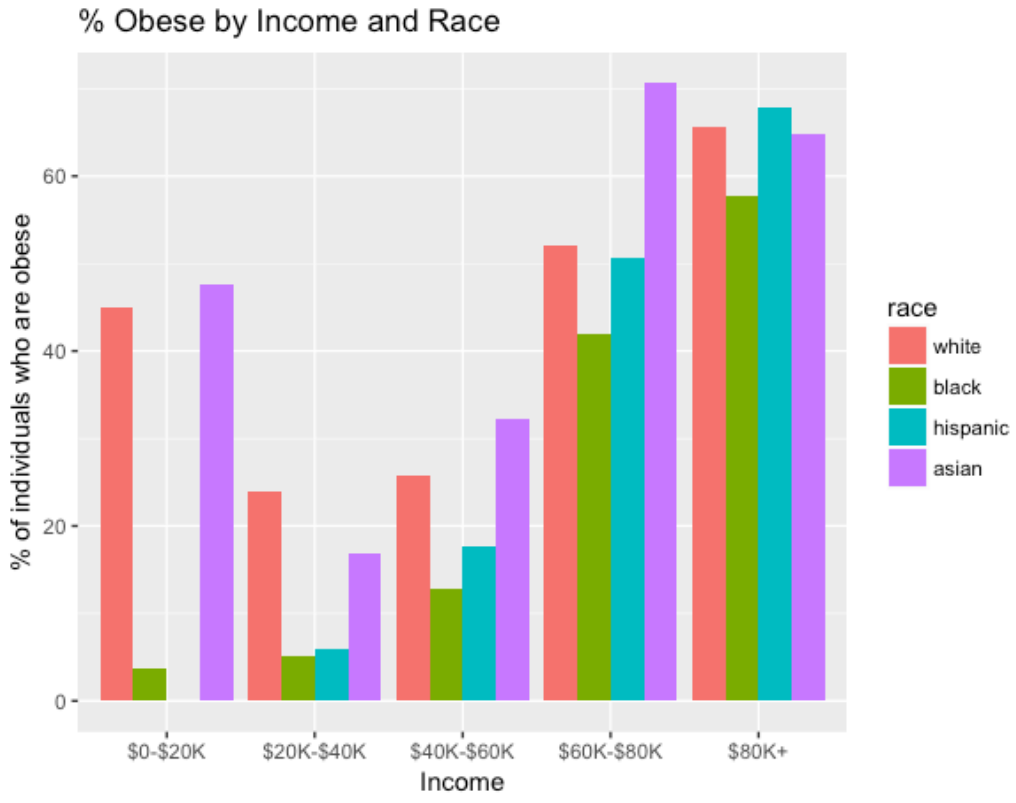


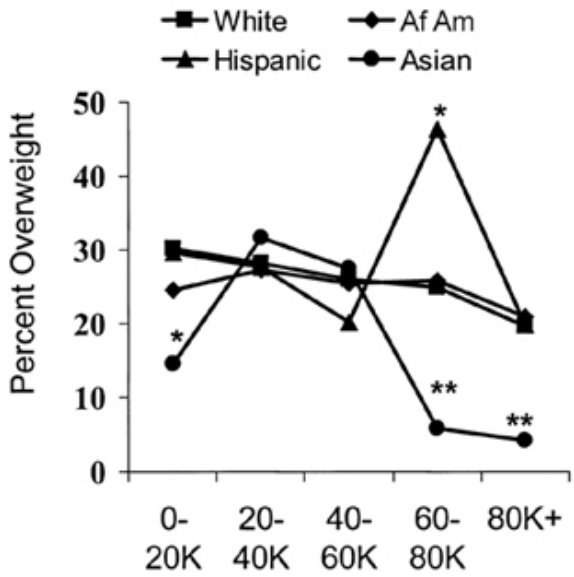
A t-test was then performed to see if there were statistically significant differences in mean BMI across sexes.

```
> t.test(data_male$bmi,data_female$bmi)

        Welch Two Sample t-test

data:  data_male$bmi and data_female$bmi
t = 9.1516, df = 9574, p-value < 2.2e-16
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.2750047 0.4249254
sample estimates:
mean of x mean of y
 25.75852  25.40855
```

The results of this t-test show that there is a statistically significant difference between the mean BMIs of men and women ($p = 2.2e\text{-}16$, CI = (0.275, 0.424)).

As there are not equivalent numbers of rows for each race the percent of those in each race that were obese needed to be calculated in order to perform chi-squared tests and to plot that data in a manner that would reflect information accurately. After creating data frames for the percent of people that were overweight for each race stratified by income level and education level I looked at differences across income levels. My plot (top) as well as the article's plot (bottom) are shown below.



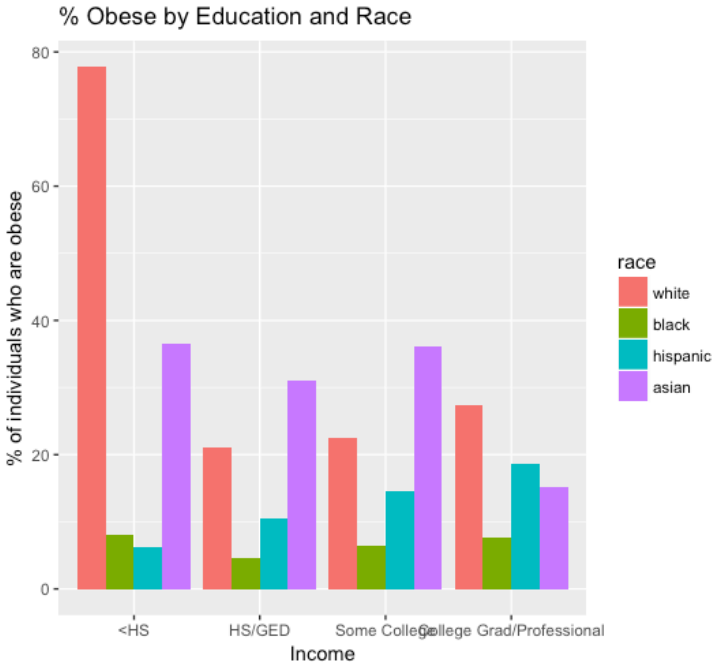


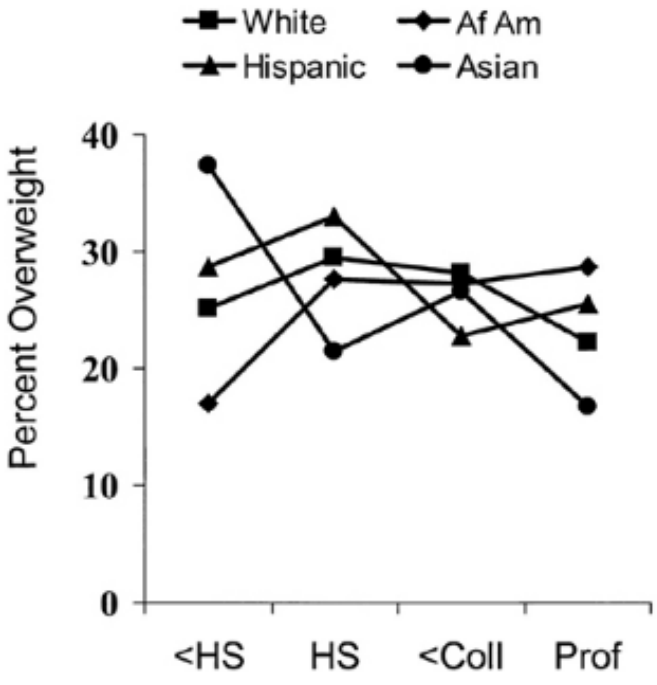
There are clearly some differences in the article's results and mine. The original research showed that there are some spikes in obesity rates at certain income levels. For example, Hispanics had a large spike at the 60-80K income level.. However, my data shows that there were much higher levels of obesity at higher income levels and a steady increase as income increases. Also, Asians and Whites in my sample had very high percents of overweight individuals at low-income levels, which differs greatly from the article's data. I performed a chi-squared test of the percents of adolescents overweight differed across income levels.

```
> chisq.test((perc_ow_race_income))

        Pearson's Chi-squared test

data:  (perc_ow_race_income)
X-squared = 47.848, df = 12, p-value = 3.321e-06
```

These results show that there is a statistically significant difference the percents of obesity across all of the income levels and races If more time was available it would be interesting to investigate the specific pairwise differences across races at each income level using.

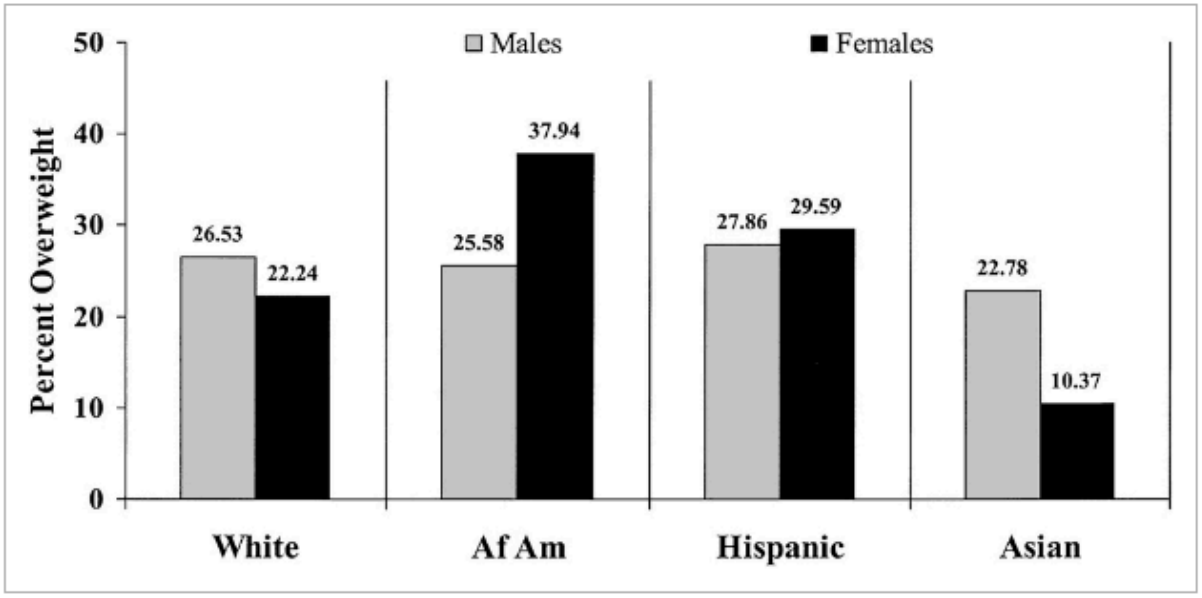
Parental education was the other categorical variable that the researchers looked at to see if there was an effect on adolescent obesity. Below are the graphs

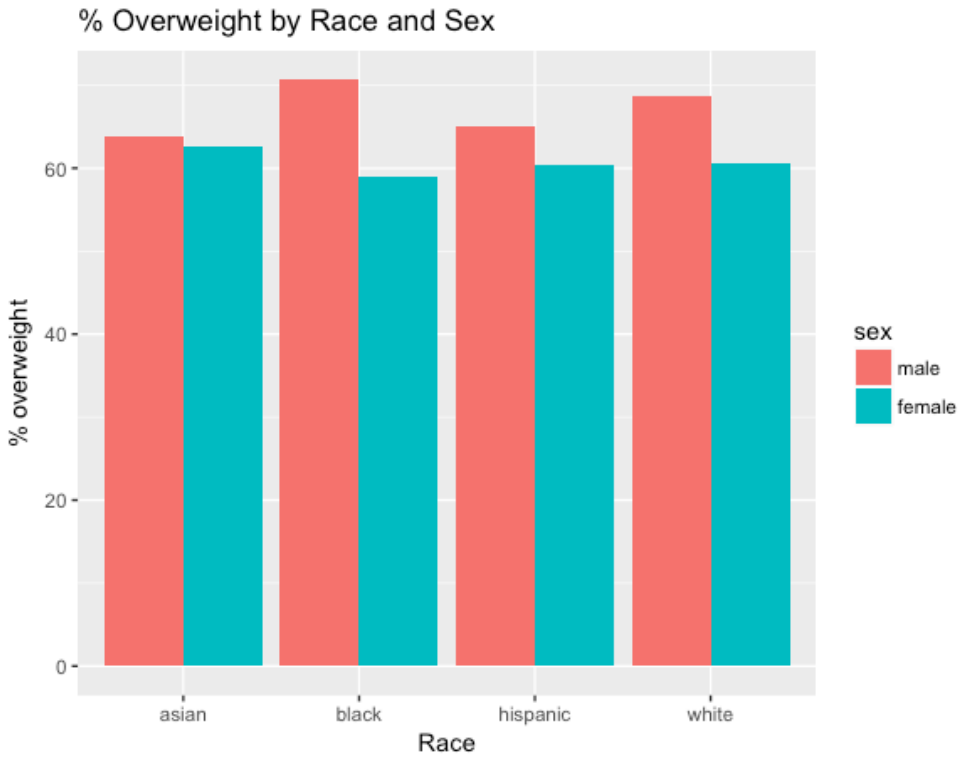




The main differences seen between the two plots is the percentage of whites whose parents had <HS education is much higher than the original data. There also seems to be a higher percentage of Asians who are obese at higher levels of parental education than in the article.

The original research also investigated the difference in percent of those overweight stratified by race and sex. The plots for the article's data (top) and my data (bottom) are shown below:





The graphs for Whites, and Hispanics for my data and the article's are all somewhat similar. However, it is clear to see that in the original research black females had a much higher percent of overweight adolescents than black males. The original research also showed that Asian males had a much greater percent of overweight adolescents than Asian females.

I performed a chi-squared test to see if the percent of overweight adolescents differed significantly across races regardless of sex. The results showed that the groups were not statistically different

```
> chisq.test(select(overweight_perc,-sex))

        Pearson's Chi-squared test

data:  select(overweight_perc, -sex)
X-squared = 0.4725, df = 3, p-value = 0.9249
```

One thing that the researchers did not look at (or at least did not report on) was the differences in percent of people that were obese across sexes. The following performed a t-test for the mean percent of people that were overweight for all races

t-test for % of People Overweight Across Sexes

```
> t.test(ow_transpose$male,ow_transpose$female)

        Welch Two Sample t-test

data:  ow_transpose$male and ow_transpose$female
t = 3.6054, df = 4.3906, p-value = 0.01932
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
  1.625225 11.061735
sample estimates:
mean of x mean of y
 67.02502  60.68154
```

These results show that there is a statistically different mean percentage of people that are overweight when compared across sex ($p = 0.01932$, CI = (1.625, 11.062)). We can reject the null hypothesis that there is not a true difference in means across sexes.

Since obesity can be classified as a binary/logical (0 or 1) variable I decided to try some logistic regression models to see if there was a strong enough correlation to perform an SVM or Clustering machine-learning model. The following logistic regression models (along with a linear model to try and predict BMI) were created.

Logistic and Linear Models

```
Call:
glm(formula = obese ~ . - height - weight, family = binomial,
    data = data)

Deviance Residuals:
     Min        1Q    Median        3Q       Max
-0.01296   0.00000   0.00000   0.00000   0.01425

Coefficients:
                                    Estimate Std. Error z value Pr(>|z|)
(Intercept)                     -84551.950 242180.968  -0.349    0.727
raceblack                           -9.893    270.332  -0.037    0.971
racehispanic                         7.731    132.084   0.059    0.953
racewhite                            2.959    247.365   0.012    0.990
educationCollege Grad/Professional  -6.918    267.116  -0.026    0.979
educationHS/GED                     -5.828    155.595  -0.037    0.970
educationSome College               -0.428    724.885  -0.001    1.000
income.level$20K-$40K                3.406    133.638   0.025    0.980
income.level$40K-$60K               -1.540    147.153  -0.010    0.992
income.level$60K-$80K               14.548    239.769   0.061    0.952
income.level$80K+                   -2.137   1334.944  -0.002    0.999
sexmale                             -5.231    134.008  -0.039    0.969
bmi                               3382.232   9688.189   0.349    0.727

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 1.3125e+04  on 9999  degrees of freedom
Residual deviance: 9.2612e-04  on 9987  degrees of freedom
AIC: 26.001

Number of Fisher Scoring iterations: 25
```

```
> glm_race <- glm(obese~race,data = data,family = binomial)
> summary(glm_race)

Call:
glm(formula = obese ~ race, family = binomial, data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4433  -1.3906   0.9330   0.9499   0.9858

Coefficients:
             Estimate Std. Error z value Pr(>|z|)
(Intercept)   0.56185    0.07832   7.174 7.28e-13 ***
raceblack    -0.07332    0.09043  -0.811    0.418
racehispanic -0.09293    0.09219  -1.008    0.313
racewhite     0.04448    0.08330   0.534    0.593
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 13125  on 9999  degrees of freedom
Residual deviance: 13116  on 9996  degrees of freedom
AIC: 13124

Number of Fisher Scoring iterations: 4
```

```
glm(formula = obese ~ income.level, family = binomial, data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4440  -1.4011   0.9324   0.9597   0.9738

Coefficients:
                     Estimate Std. Error z value Pr(>|z|)
(Intercept)           0.53635    0.04573  11.730   <2e-16 ***
income.level$0-20K   -0.03180    0.09141  -0.348    0.728
income.level$20K-$40K  0.07146    0.05873   1.217    0.224
income.level$40K-$60K -0.02433    0.06328  -0.385    0.701
income.level$60K-$80K  0.05238    0.08060   0.650    0.516
income.level$80K+    -0.03656    0.08529  -0.429    0.668
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 13125  on 9999  degrees of freedom
Residual deviance: 13120  on 9994  degrees of freedom
AIC: 13132

Number of Fisher Scoring iterations: 4



Call:
glm(formula = obese ~ education, family = binomial, data = data)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.4315  -1.4114   0.9431   0.9602   0.9656

Coefficients:
                                 Estimate Std. Error z value Pr(>|z|)
(Intercept)                       0.52097    0.04888  10.657   <2e-16 ***
educationCollege Grad/Professional  0.05890    0.06485   0.908    0.364
educationHS/GED                   0.04763    0.06135   0.776    0.438
educationSome College             0.01395    0.06326   0.221    0.825
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 13125  on 9999  degrees of freedom
Residual deviance: 13124  on 9996  degrees of freedom
AIC: 13132

Number of Fisher Scoring iterations: 4
```

```
> lm_all <- lm(bmi~.-obese-height-weight,data = data)
> summary(lm_all)

Call:
lm(formula = bmi ~ . - obese - height - weight, data = data)

Residuals:
    Min      1Q  Median      3Q     Max
-8.9691 -1.2360  0.0713  1.3087  6.6106

Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)
(Intercept)                       25.40676    0.09633 263.737   <2e-16 ***
raceblack                         -0.03738    0.08496  -0.440    0.660
racehispanic                      -0.08241    0.09355  -0.881    0.378
racewhite                          0.07495    0.07683   0.976    0.329
educationCollege Grad/Professional -0.01101    0.06201  -0.178    0.859
educationHS/GED                   -0.02061    0.05839  -0.353    0.724
educationSome College             -0.02744    0.06068  -0.452    0.651
income.level$0-20K                 0.04061    0.10576   0.384    0.701
income.level$20K-$40K              0.05812    0.05643   1.030    0.303
income.level$40K-$60K             -0.03279    0.06108  -0.537    0.591
income.level$60K-$80K             -0.02560    0.07604  -0.337    0.736
income.level$80K+                 -0.12331    0.08115  -1.520    0.129
sexmale                            0.34701    0.03805   9.119   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 1.898 on 9987 degrees of freedom
Multiple R-squared:  0.009798,  Adjusted R-squared:  0.008608
F-statistic: 8.235 on 12 and 9987 DF,  p-value: 1.152e-15
```

The model using all of the predictor variables as well as models using each of the possible predictor variables individually (excluding height and weight as these are directly used to calculate BMI) did not produce any significant predictive p-values. I expected this from my data, as there was not much variation when looking at the distributions of BMIs across each of the predictor variables. Therefore, I decided to forgo trying to fit a SVM or clustering machine learning model to the data. The linear model's extremely small R-Squared value (0.008608), the residual vs. fitted plot, and Q-Q plot showed that a linear model was not a good fit in trying to predict BMI of an individual.

Overall, I consider my simulation a success. As I was able to recreate the proper distributions of sex, race, income level, and parental education. However, since the original data set was created from a random sample of the entire adolescent population of the United States - and then I tried to recreate it using what sample parameters were available - it should be expected that there would be a good amount of variation in the original and my simulated version. If more variables had been collected during the original research such as the distribution of ages, parent ages, and activity levels it may have been possible to glean more predictive value from the analysis of the data.