

Predicting Contributing Factors to Diabetes.

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## Predicting Contributing Factors to Diabetes.

### I. Introduction

Diabetes has long plagued the world, but within the past 60 years, the number of people affected by this disease has increased dramatically. The CDC estimated that in 2015, just under 8% of the United States population was diagnosed with diabetes. According to a brief time series analysis of the historical data that the CDC publishes from 1980 to 2017, the rate of diabetes is continuing to grow. An ACF plot found that at four lags in, the present values for the total percentage of the population with diabetes is well related with the past total percentage reports. If we are to continue on this path, we could see changes within the healthcare and pharmaceutical industries that may not be for the best.

To further explore this, we are using a dataset from the National Health and Nutrition Examination Survey. The "survey" is actually a group of surveys, each designed to "assess the health..of adults and childre in the United States." While some surveys are very much qualitative information, the data that we will be analyzing is purely quantitative.

The NHANES program began in the 1960's, and is a major program section at the Centers for Disease Control and Prevention. It is used by both government and institutional analysts to find patterns in the approaches to and general sentiment towards healthcare and nutrition domestically. Because of its comprehensive nature, it is widely applicable for modeling and predicting patterns in many diifferent fields. The data has been used to create growth charts for children, develop the policy to remove lead from common household items, influence immunization schedules, and track diabetes. All of the data is collected and anonymized to protect the healthcare rights afforded by HIPPA.

While some of this data can be used in isolation, say to determine the rates of change in diabetes diagnoses, more comprehensive data can be used to holistically determine if there are leading causes in diabetes, including changes which may not have been foreseen at the beginning of the data collection, but which is due to more than just chance.

The NHANES dataset were retrieved in a cleaned form from the Kenyon College department of statistics. The dataset originally included about 10,000 observations across 70 different variables. The applicable dataset was cleaned to only include 2167 observations across 28 different variables. The data includes observations gathered from 2009 to 2012's biannual surveys, and the dataset was filled on a rolling schedule.

### III. Methods

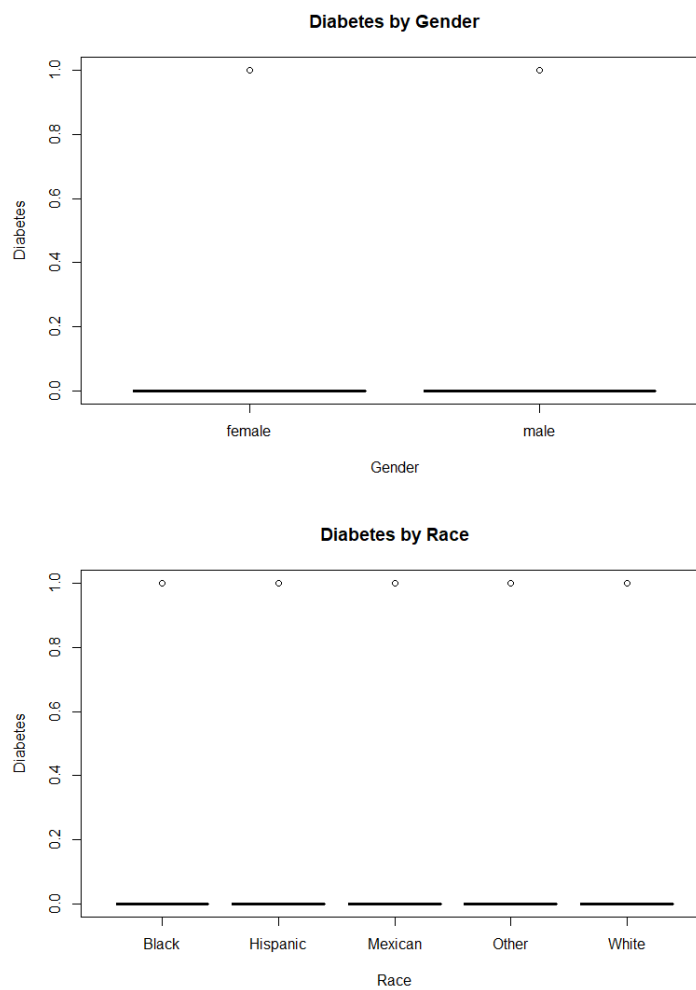
Analysis began by exploring the data graphically. To determine if there were any variables that were heavily correlated with each other, a numerical correlation matrix and the accompanying  $p$ -value matrix were created. In analyzing this correlation matrix, I tagged correlations which had a correlation  $cor > 0.25$  and  $p > 0.05 = \alpha$  to find if any of these variables were heavily correlated with each other, and whether those correlations were due to more than just chance. Given a dataset with this many variables, some overlap and high correlations between variables is to be expected.

The correlations that were found did make sense. The variable *HomeRooms* was correlated to *HHIncomeMid*, which makes sense because as income increases, the number of rooms in your home would also increase. *Height*, *Weight*, and *BMI* are all highly correlated, which makes sense, since BMI is derived from both height and weight, by the CDC's definition<sup>1</sup>. As expected, average diastolic blood pressure (*BPDiaAve*) and average systolic blood pressure (*BPSysAve*) are also related. Of note is that only the average systolic blood pressure is somewhat highly correlated with age, not average diastolic blood pressure. Finally, the first urine flow rate measurement (*UrineFlow1*) is somewhat highly correlated with the volume of urine (*UrineVol1*). There were no other variables which had a high correlation that were also significant. Plots were made for most of the variables, against the binary variable *Diabetes*. The expected behavior here was that for any given boxplot, the majority of every group would be within the box, which should have been clustered around 0. Some groups may have had an outlier of diabetics, if the variable were

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<sup>1</sup>Of note is that the CDC does NOT take into account the gender, but different BMI models may take this into account. For the purposes of this study, gender is not used.

to be significant or heavily correlated, which would show up in any boxplot as a group of outlier points where *Diabetes* = 1. Several of these plots are given as follows.



### III. Results

### V. Conclusion

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