What Does McDonald's Say About Your City?

Looking for trends in McDonald's Yelp Reviews, diabetic rates, and Census statistics

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Abstract

Yelp offers a plethora of data about consumer expectations. Each year, users leave tens of millions of reviews to let others know about their experience. We mine reviews on over 13,000 McDonald's restaurants and cross reference this information with geographic diabetic rates and Census statistics. We look for relationships between McDonald's reviews and sociological factors such as poverty rates, income per capita, and population density. We also explore relationships between McDonald's and areas with diabetes. We employ single and multivariable regressions to identfy these relationships.

Our results show McDonald's presence is significantly correlated with the wealth of a city (and its citizens) as well as diabetic rates. Despite this strong correlation (all p values < 0.01), McDonald's data does not hold predictive power for diabetic rates or the wealth of an area. Interestingly, we discover that the wealth of an area can reasonably predict (R squared = 40%) the rate of diabetes in an area.

Background & Motivation

There have been dozens of studies on the direct effects of fast food (and particularly McDonald's) on an individual's body. As data has become available, statisticians have taken a more macro perspective and tried to map the effects of McDonald's on a population as whole (Morgenstern, 2009).

Today services such as Yelp offer not only business locations and details, but also reviews of performance, all completely free to view and download. Previous research fails to discuss *satisfaction* of a restaurant and its relationship with an individual's health. In other words, the question remains unanswered: Do people's satisfaction rates with McDonald's provide any indication of their health level? Answering this question would mean measuring the impact of McDonald's on a population, instead of just individuals.

Data Mining Yelp

Prior to any data collection, we were determined to organize our information geographically in order to find trends by location. Our other two datasets (diabetes statistics from the CDC and socioeconomic details from the 2010 US Census) are already organized by county. Because there are over 3,000 US counties, we felt US counties were sufficiently granular and should aggregate Yelp reviews on McDonald's by county as well.

Using a list of latitude/longitude coordinates of all US counties; we search for McDonald's in all 3,000 counties and store up to 20 locations per search (limited by Yelp). While there were dozens of fields of data for each McDonald's, we were only interested in customer reviews and locality. Hence, we only store information pertaining to user reviews or the physical location of a store. We then combine McDonald's data with CDC and Census dataset and organize all information by county.

Dataset

Yelp's v1 API, though deprecated, allowed us to make thousands of calls to its business API to access a wealth of information. We parsed the JSON and store the following attributes *per store* *(per McDonald's)*. Note: We also use datasets available by the US Census Bureau and Center for Disease and Control. Attached code for mining Yelp is in the appendix.

Data Stored Per McDonald's Location (Yelp):

- Average Rating
- Number of Reviews
- Latitude Coordinate
- Longitude Coordinate
- City
- County ID (Also known as FIPS Number)

Data Stored for Each US County (Census and CDC):

- Population
- Percent of Population Female
- Median Home Value
- Income Per Capita
- Percent of Population in Poverty
- Population Density
- People Diagnosed with Diabetes out of every 1000 People

Methodology

Once our data was compiled and stored in a single location, our primary method to identify relationships was using single and multivariable regressions. While we implemented the regression functions ourselves in Matlab, we display the results from our work in Excel for ease of presentation.

Single Regression

We first look for correlation between two variables. Interestingly, almost all of the census statistics were significantly correlated with diabetes rates as well as McDonald's locations. In general, we find that the percentage of females in a city does not correlate with any of our variables, and we remove it from future analysis.

In determining which variables had meaningful (statistically significant) relationships, we mainly observe R^2 values and p-values. While we accept that R^2 values will not be high for most regressions, we only consider a relationship noteworthy if the p=value was less than 0.05.

The code implementation for the single variable regression can be seen in the following section, "Multiple Regression", and in the file named **singleregression.m**.

Multiple Regression

Our approach to multiple regressions was more sophisticated than that of single regressions due to the sheer number of combinations we could possibly run. Our main algorithm for selecting multiple regression variables began by running a regression on the entire dataset. We then individually eliminate variables that were not statistically significant (p-value < 0.05) and observe R^2 values. Ultimately, we sought to maximize R^2 values while keep all components of the regression statistically significant.

The implementation can be found in **multivarregression.m**. Implementing both regressions is essentially the same mathematically. The only difference is the number of columns in X which increases for each additional X variable. The program outputs the w values corresponding to the equation yi ≈ w0 + w1 xi.., where the given x corresponds to the given variable.

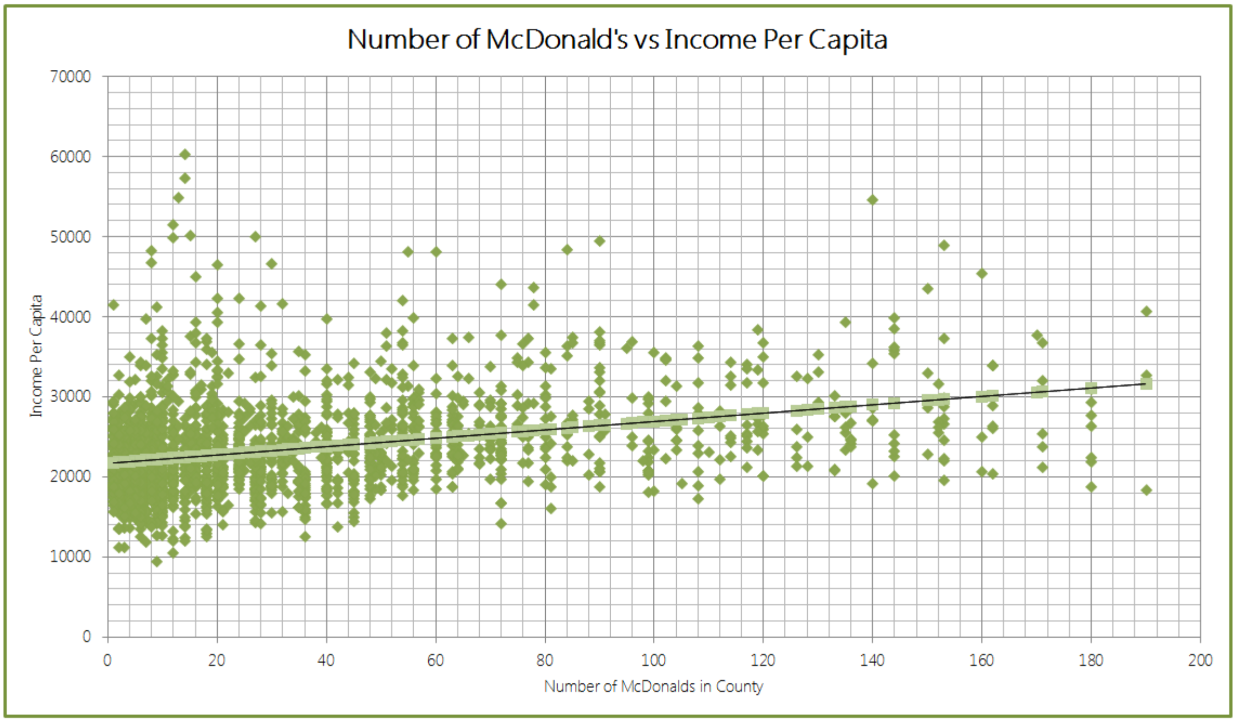
Identifying Underlying Relationships

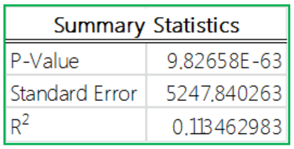
It is easy to regress variables and assume they are uniquely correlated due to low p-values, and so we look for relationships between all 3 of our datasets before assuming that 2 of them are uniquely related. We discuss this component of our analysis further in our Results.

Results

Overall, we discovered several interesting trends related to McDonald's as a company as well as diabetic rates across the US. We focus our efforts on new information that hasn't been found. For example, there has been extensive research on poverty effects on health, and thus it is no surprise that lower income areas have higher rates of diabetes (and probably other medical conditions). We identify five major relationships as outlined below.

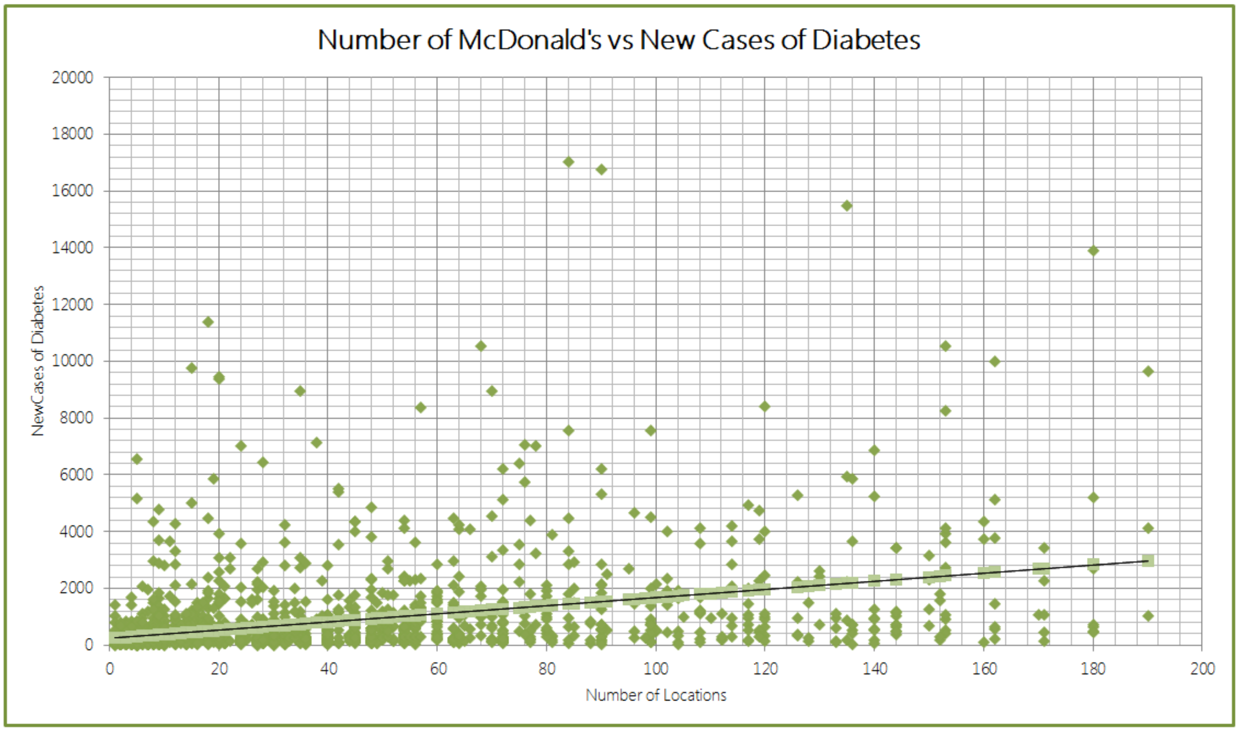
Exhibit 1: Number of McDonald's in a County is Correlated With Income Per Capita

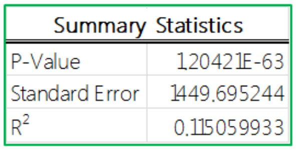




Summary Statistics	
P-Value	9.82658E-63
Standard Error	5247.840263
R^2	0.113462983

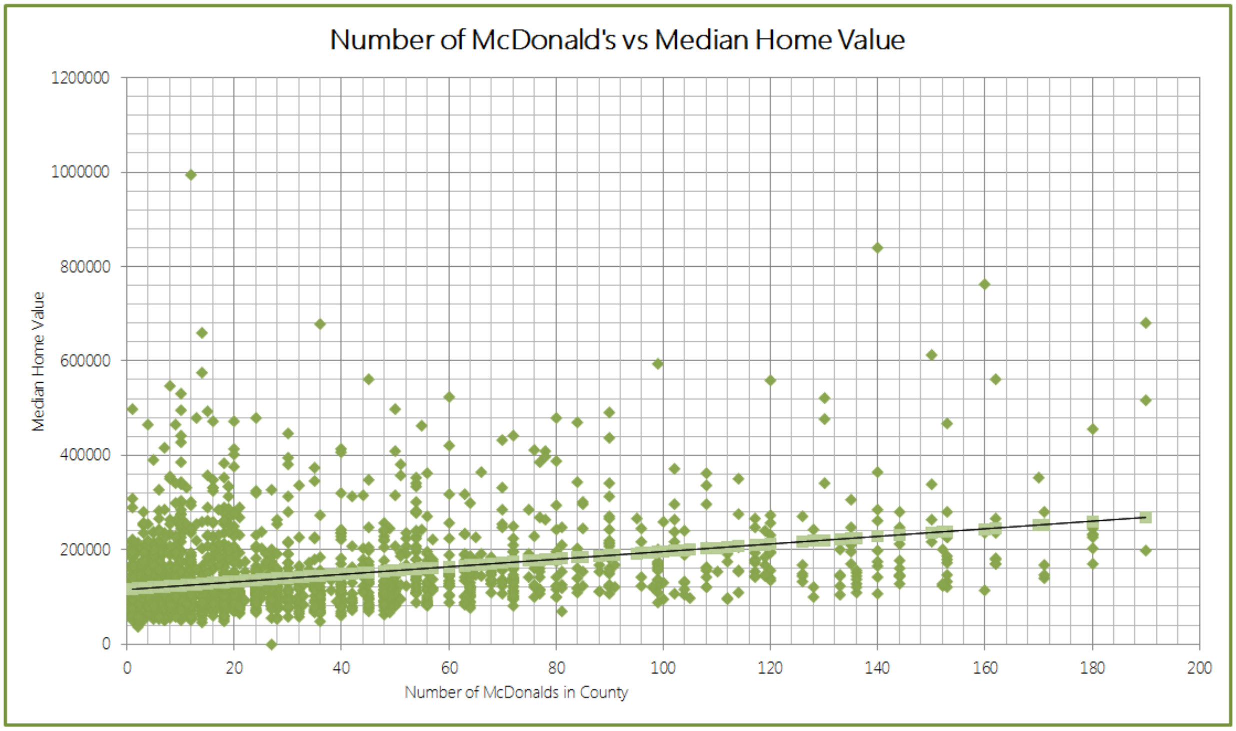
Exhibit 2: Number of McDonald's Correlated with New Cases of Diabetes in a County

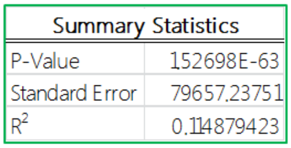




Summary Statistics	
P-Value	1.20421E-63
Standard Error	1449.695244
R^2	0.115059933

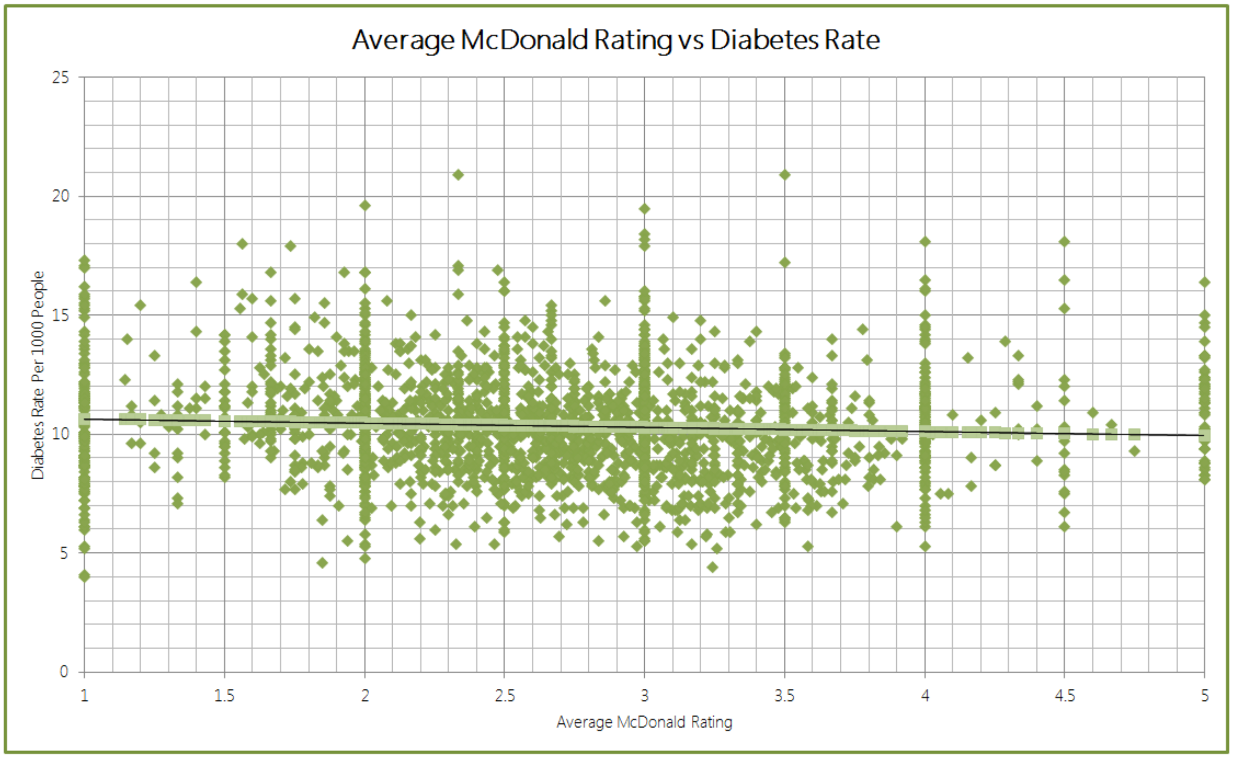
Exhibit 3: Number of McDonald’s Correlated with Median Home Value

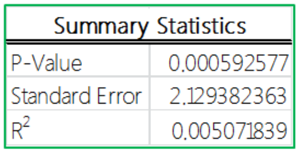




Summary Statistics	
P-Value	1.52698E-63
Standard Error	79657.23751
R^2	0.114879423

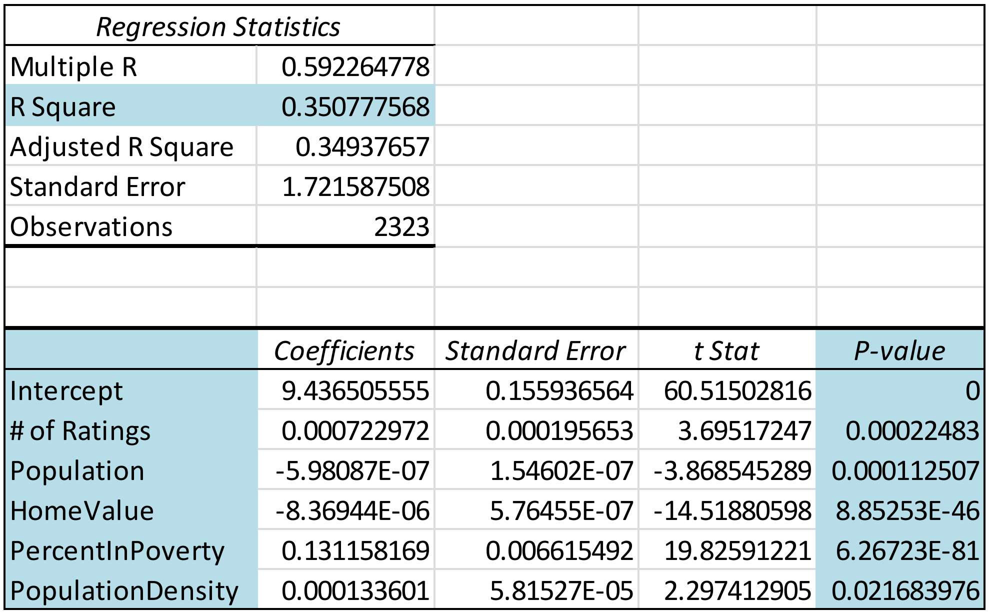
Exhibit 4: McDonald’s Rating is Inversely Correlated with Diabetes Rate





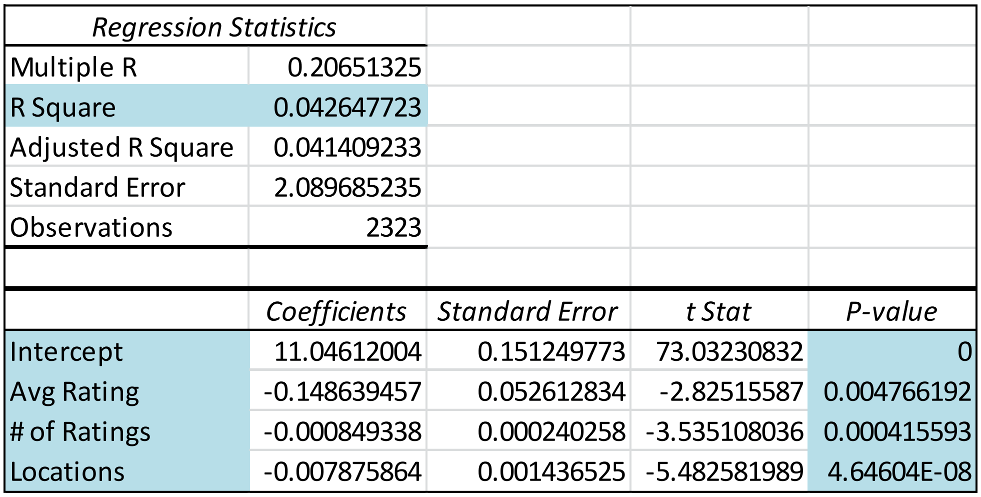
Summary Statistics	
P-Value	0.000592577
Standard Error	2.129382363
R^2	0.005071839

Exhibit 5: Census Statistics Can Partially Explain Diabetes Rate



Regression Statistics				
Multiple R	0.592264778			
R Square	0.350777568			
Adjusted R Square	0.34937657			
Standard Error	1.721587508			
Observations	2323			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	9.436505555	0.155936564	60.51502816	0
# of Ratings	0.000722972	0.000195653	3.69517247	0.00022483
Population	-5.98087E-07	1.54602E-07	-3.868545289	0.000112507
HomeValue	-8.36944E-06	5.76455E-07	-14.51880598	8.85253E-46
PercentInPoverty	0.131158169	0.006615492	19.82591221	6.26723E-81
PopulationDensity	0.000133601	5.81527E-05	2.297412905	0.021683976

Exhibit 6: McDonald’s Data is Correlated with Diabetes, Though it Holds Little Predictive Power



Regression Statistics				
Multiple R	0.20651325			
R Square	0.042647723			
Adjusted R Square	0.041409233			
Standard Error	2.089685235			
Observations	2323			
	Coefficients	*Standard Error*	*t Stat*	*P-value*
Intercept	11.04612004	0.151249773	73.03230832	0
Avg Rating	-0.148639457	0.052612834	-2.82515587	0.004766192
# of Ratings	-0.000849338	0.000240258	-3.535108036	0.000415593
Locations	-0.007875864	0.001436525	-5.482581989	4.64604E-08

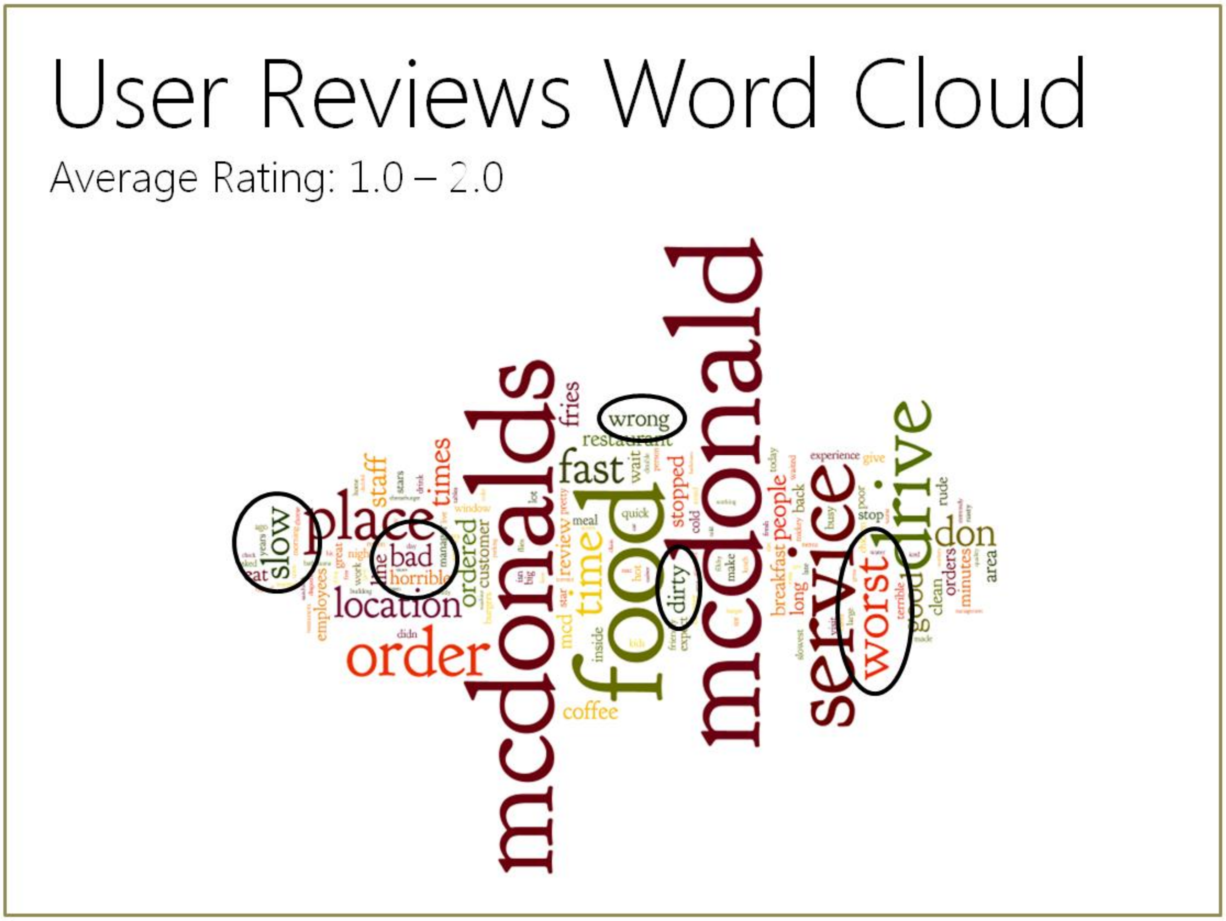
Discussion

Many of our results were in tune with intuition and some even countered our original hypothesis. Overall, we find that Census statistics have strong predictive power for many elements in our dataset, ranging from the number of Diabetes cases in an area to how well McDonald's was rated on Yelp. For this reason, we had to be careful not to attribute variable to McDonald's when they were actually correlated with Census statistics.

Revising Our Original Assumption

As mentioned previously, our motivation for this project was to see if we could prove citizens in different areas have different expectations for the same service. The initial assumption was that McDonald's offers a homogenous experience across all of its locations, and the variance in reviews would be a function of different levels of expectations amongst customers. If this were the case, we would expect lower areas to rate McDonald's higher than more wealthy areas. We quickly realized, however, that this was not the case. Wealth of a region affects the quality of McDonald's service. To illustrate this, we generate word clouds using the reviews users left for McDonald's of different levels.

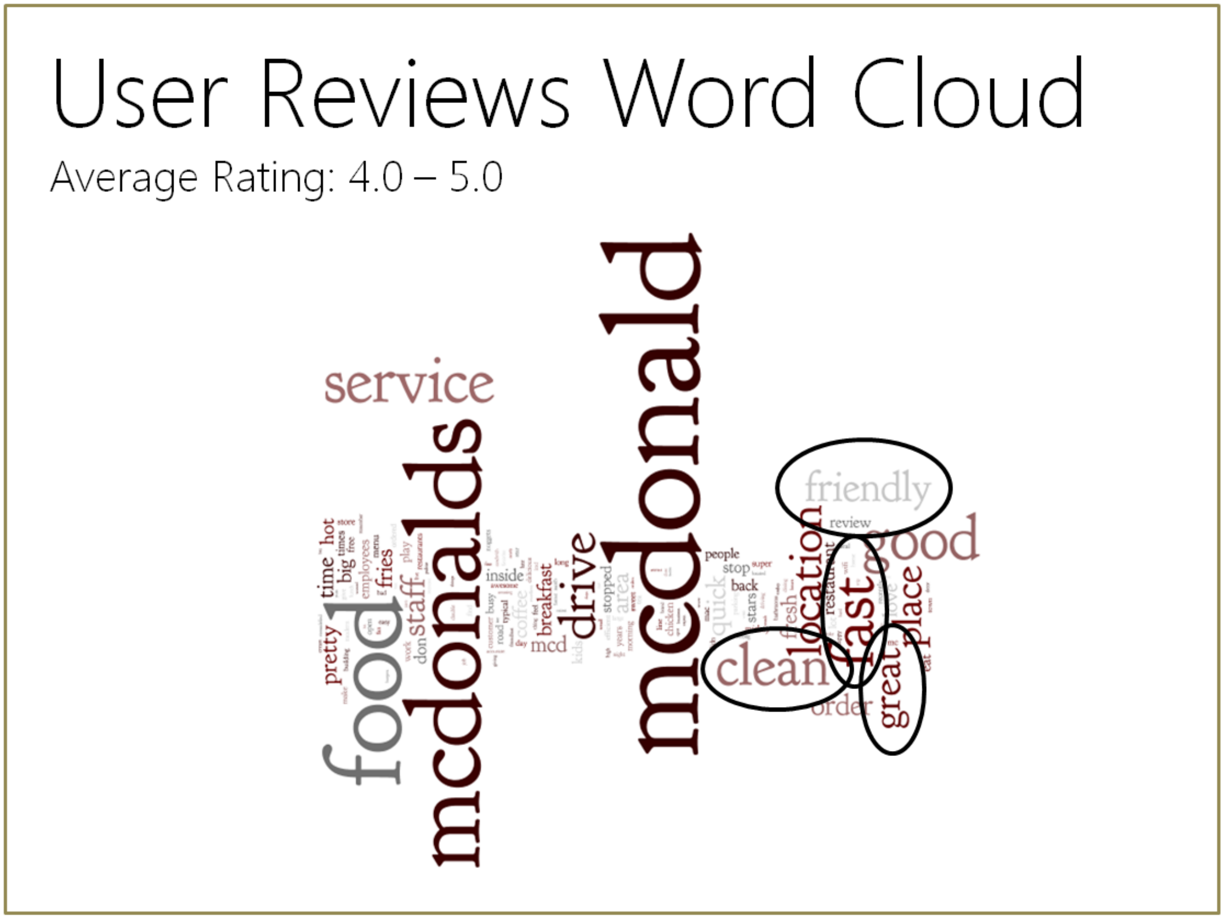
Exhibit 7: Word Cloud of McDonald's Reviews Rated 1.0 – 2.0



User Reviews Word Cloud

Average Rating: 1.0 – 2.0

Exhibit 8: Word Cloud of McDonald’s Reviews Rated 4.0 – 5.0



User Reviews Word Cloud

Average Rating: 4.0 – 5.0

As you can see, there is a stark difference in the vocabulary of both reviews, identifying that there was a stark difference in customer experience at both locations.

McDonald’s Locations Positioned to Most Profit

We found that McDonald’s locations can be most explained by factors that are could boost its sales. This makes plenty of sense, as that is McDonald’s goal as a business. We find that McDonald’s locations are most correlated with measures of wealth seach as income per capita and median home value. While this relationship was not surprising, we believe there is still value in quantifying it

McDonald’s and Diabetes

We found that the number of McDonalds in an area and the number of new cases of diabetes in an area are highly correlated. In hindsight, this correlation seems to be obvious, as McDonalds has a reputation of being unhealthy and is commonly associated with diseases such as this. This does not mean specifically that McDonalds can be blamed for causing these new cases of diabetes, only that there is a correlation here.

McDonald’s Rating and Diabetes

Our most interesting finding was the inverse relationship between diabetes rates and McDonald’s ratings. We found that poor McDonald’s reviews indicate higher levels of diabetes in an area. While this observation is counter-intuitive, we closely examined the data in order to understand this relationship. We found that in low income areas, diabetes rates are higher than usual and McDonald’s reviews are lower than usual. For this reason, our analysis also identified a relationship between diabetic rates and ratings. We found this lesson to be valuable from our project, as it illustrates the importance of human insight vs blind statistical analysis.

Future Studies

While our analysis revealed interesting information, we believe this study could be further expanded to provide even more information. Specifically, we feel that only observing McDonald’s in counties is a one-dimensional approach to analysis. It would be more interesting to incorporate other unhealthy food chains. We also see merit in looking for trends in more than just diabetics, after all diabetes is only one of the diseases McDonald’s exacerbates.

We look forward to future literature about the subject matter. As data collection and analysis becomes even more ubiquitous, we believe there will be more answers explaining obesity and its socioeconomic causes.