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Detroit Crime Data Audit

Sections

1228 words without statistics

Introduction

When thinking about utilizing artificial intelligence to automate tasks, it becomes important to understand the cultural context that the algorithm is used for- especially if it is taking into consideration a rich variety of data with life threatening ramifications. Many companies have made it to the front of the news when they forgot to consider these factors, such as HireVue, a company which makes use of AI to screen users' virtual video interviews in order to understand who would make good interns or employees. It was found through an audit that HireVue's algorithm discriminated against individuals with disabilities by sensing tone of voice and facial expressions, which led to outrage among disability advocates *(Whitaker et. al)*. HireVue is one of many corporations who take part in this behavior; companies leverage their data and technology to label individuals based on an associated group they are in, which is used to assess their capabilities or future actions. Unless discovered through an audit, companies tend to avoid discussing these issues in order to hold onto this sense of power and prevent scrutiny in the public eye *(Pasquale)*. There have been many occasions as well, when varying levels of the government made use of algorithms in order to make decisions with little human oversight. An example of this is Northpointe's crime algorithm, which is used to estimate the likelihood of an individual committing a crime again. Oftentimes, the results were misleading and discriminated against people of color. When people of color commit a smaller crime, it is often weighed to be the same likelihood of a white individual who committed an arguably heavier offense *(Angwin et. al)*. The data that this algorithm and others mentioned all have in common is that the training data for the machine learning models were biased or not trained correctly, which would lead to disruptive results due to the algorithms favoring certain demographics over others *(Miceli et. al)*. My interest in this topic was sparked by reading up on the case of Robert Julian-Borchak, who was falsely accused and arrested by Detroit police. The police were making use of facial tracking software in order to track a suspect who shoplifted from a boutique. When detectives learned that Robert did not commit the crime, their only response was: "I guess the computer got it wrong" *(Hill).*

For this project, I decided to audit a variety of different datasets that are being used by Detroit in order to detect hotspots for crime. My main priority was to determine whether there were racial trends within this data. Determining this would help me understand if this data set contributed to the racial discrimination within a variety of algorithms Detroit has used, such as the facial recognition software. To help arrive at this conclusion, there were five different questions that I explored when analyzing the data. Some of these questions focused on trying to understand if there are extraneous factors apart from race that may be impacting the data used to train algorithms, such as time, weekday, and population. Attached below are all 5 questions:

1. Does Detroit crime data have unequal rates of representation between precincts, scout car regions, or neighborhoods?
2. Do regions with more representation in the training data have more representation due to these locations having a larger population?
3. Are the main factors/trends that this data focuses on is the population, hour of day, or day of week impact when crime occurs?
4. What is the largest racial demographic per region in Detroit, and is there a bias in the data when identifying a trend between racial populations in regions for certain races more than others?
5. Does there tend to be a trend in which some racial population distributions are impacted by other racial population distributions?

Statistics

There were 5 different sources of data that I made use of for this project, with 4 of the sources coming from Data Driven Detroit- a site which hosts a variety of data tables that are used in helping develop different algorithms (Data Driven Detroit). 3 of these datasets are shape file maps, which allows me to assess crimes committed in Detroit based on precinct, scout car area, and neighborhood. The 4th dataset from Data Driven Detroit provides data about different crime cases that have occured in Detroit from 2018-2023, and their location, time of day, etc. The last dataset I made use of is a race shape map, which allows me to figure out the racial distribution and population of Detroit.

Question 1: Does Detroit crime data have unequal rates of representation between precincts, scout car areas, or neighborhoods?

For my first question, I explored crime data by plotting how often crime cases occur in scout car areas *(Figure 1A)*, neighborhoods *(Figure 2A)*, and precincts *(Figure 3A).* Each map showed a mix of areas with a lot of crime and low in crime. I checked for spatial autocorrelation next in order to get quantifiable numbers for data, which in this scenario, would assess whether crimes were spread out among all regions or whether crimes in Detroit were focused in specific regions. A ‘I value’ close to -1 would mean that the data is distributed evenly across the map, close to 0 would mean that the data is scattered randomly, and close to 1 would mean that the data is focused in specific regions. A ‘p value’ less than 0.05 would mean that we can state with 95% confidence that there is a non random relationship between the variables analyzed in (alternative hypothesis), while greater than 0.05 means that we can not prove a non random distribution in the data (null hypothesis).

For scout cars *(Figure 1B)*, the I value was 0.11 and p value was 1.26 x (10^-8). For neighborhood *(Figure 2B)*, the I value was 0.047 and p value was 0.003. Lastly for precincts *(Figure 3B)*, the I value was -0.09 and p value was 0.99. Evaluating these results meant that for both scout cars and neighborhoods, we can say with 95% confidence that there is a non-random correlation between crime locations and scout car areas/neighborhoods, but the strength of this non random relationship, although positive, is weak. This is due to the I value being close to 0 and p value being less than 0.05. As for precincts, we fail to state with 95% confidence that there is a non random trend within the spread of data. Reasons behind the different results of scout car areas/neighborhoods and precincts may be the fact that precincts are broken into less regions than the other 2 aspects on the Detroit map. In conclusion, we can state that scout car areas and neighborhoods have slightly unequal distribution of crime with not much impact on data, while police precincts do not have unequal distribution.

Question 2: Do regions with more representation in the training data have more representation due to these locations having a larger population?

Similarly, I did an auto-correlation test on the amount of houses scattered throughout Detroit to determine whether the reason behind the slightly unequal distributions could be explained partially by unequal populations throughout different locations in Detroit *(Figure 4).* An I value of 0.14 indicates that houses are slightly concentrated in certain regions of Detroit more than other neighborhoods, while a p value of 0 indicates that we can say with 95% confidence that there is a non random population distribution throughout Detroit. In conclusion, we can state that the population distribution of Detroit is slightly concentrated.

Question 3: Are the main factors/trends that this data focuses on is that the population, hour of day, or day of week impact when crime occurs?

For this question, I did linear regression tests in order to figure out if location data (zip code, scout car area, neighborhood, council district, and precinct) have an influence on three different variables- population, hour of crime, and day of week for crime. If I got an R value close to 1, that would mean there is a strong relationship between location data and the variable in question. An R value close to 0 means that there is a weak, or no relationship between location data and the variable in question. For homes/population, I got an R value of 0.912 *(Figure 5)*. For hour of crime, I got an R value of 0.005 *(Figure 6)*. For the day of week, I got an R value of 0.004 *(Figure 7)*. I found, in conclusion, that the population has a strong relationship with zip code, scout car area, neighborhood, council district, and police precinct. I also found that hours of crime and day of week have a very weak/no relationship with this location based data.

Question 4: What is the largest racial demographic per region in Detroit, and is there a bias in the data when identifying a trend between racial populations in regions for certain races more than others?

For this question, I first created a map that shows what the primary demographic is at different locations in Detroit *(Figure 8)*, and the population of Detroit in these different regions labeled for primary demographic *(Figure 9)*. Although there was a slight trend, I had to perform a linear regression test to verify the information in quantifiable numbers *(Figure 10)*. There was an R Value of 0.927, which means that there was a significant positive relationship between demographic counts per region (White, African American, Hispanic, and Asian) in comparison to the crime count per region. Then, I wanted to break down the data and focus on specific demographic counts per region in comparison to crime count per region. When doing a linear regression to find the relationship between African American Count and crime count, I got an R value of 0.757 and P value of 0, which means with 95% confidence, we can say there is a strong relationship between crime count and African American count within this training data *(Figure 11)*. For White Count and crime count, I got an R value of 0.262 and P value of 0, which means we can say with 95% confidence that there is a weak relationship between crime count and white count *(Figure 12)*. For Asian Count and crime count, I got an R value of 0.016 and P value of 0.264, which means we fail to say that there is a relationship between Asian Count and crime count *(Figure 13)*. For Hispanic Count and crime count, I got an R value of 0.147 and P value of 0.001, which means we can say with 95% confidence that there is a weak relationship between crime count and Hispanic count *(Figure 14)*. In conclusion, this question showed that there is a strong relationship in this data table between crimes committed and African American Population, a weak relationship between crimes committed and White and Hispanic Population, and no relationship between crimes committed and Asian Population.

Question 5: Does there tend to be a trend in which some racial populations are impacted by the population of other races in the neighborhood?

Lastly, I ran linear regression tests in order to figure out how the population of races throughout Detroit impacts the population of other races throughout Detroit. When checking how African Americans get impacted by other races I got 0.073 *(Figure 15).*

For White, I got 0.596 *(Figure 16)*. For Hispanic, I got 0.544 *(Figure 17)*. For Asians, I got 0.164 *(Figure 18)*. In conclusion, the African American population distribution in Detroit is impacted very little by other racial demographics. Asian population distributions are impacted slightly by other racial demographics. Hispanic and White population distributions are impacted moderately by other racial demographics.

Results

Within neighborhoods and scout car areas, there is a slightly unequal distribution of crime. However, it is not substantial. Police precinct regions did not have unequal distribution, which can likely be attributed to the fact that there are less regions of data in comparison to neighborhoods and scout car areas. As a result, it can likely be stated that neighborhoods and scout car areas are not the deciding factor on whether crime will occur in a region or not, which reduces extraneous factors.

Upon analyzing population data, it was found that Detroit's population is largely equal throughout the city, but with certain areas being slightly more concentrated. This could partially explain why some neighborhoods and scout car areas have more crimes than other areas.

After learning about the population being slightly skewed, I examined what factors contributed to this. It was discovered that the population distribution has a strong relationship with location based data of where crimes occur most often, such as zip code, scout car area, neighborhood, council district, and police precinct. Often, these areas have a higher concentration of individuals. Due to the higher population in some areas, this may also contribute to the reason for the higher crime rate in these locations. However, location based data had no relationship with the hour the crime occurred, nor the day of week.

Upon analyzing the distribution of crime relative to different racial demographics, it was found that there was a strong relationship in this data table between crimes committed and African American Population. There was a weak relationship between crimes committed and White and Hispanic Population, and no relationship between crimes committed and Asian Population. Because there was a strong correlation between regions with higher African American Population and greater crimes committed, this proved one of the most important aspects of my audit, which was to discover whether the data had racial trends.

Lastly, it was found that the African American population distribution in Detroit is impacted very little by other racial demographics. Asian population distributions are impacted slightly by other racial demographics, while Hispanic and White population distributions were impacted moderately by other racial demographics. This may be connected to the idea that individuals live in regions where neighbors or fellow residents are of the same race, or it could be linked to the idea that crime rate possibly varies by demographic in terms of the population.

Summary

It was discovered that the population in regions of Detroit has a positive correlation with the crime rate in the same region. It was also discovered that some racial demographics, excluding Asians and African Americans, try to live in the same regions as people of their same racial demographic. Lastly, I was able to discover that the dataset containing a training set of crimes in Detroit were racially biased, focusing more on crimes related to African Americans followed by White, then Hispanic, and lastly Asian.

The Detroit crimes training dataset originally did not have any data related to race. Instead, it required me to merge the data with other datasets in order to discover trends about the data having a racial bias towards some races more than others. It serves as a reminder that it is important to not assume that algorithms are made for the betterment of society- it helps out certain groups at the cost of other groups. Oftentimes, algorithms are created in a way so that it doesn’t directly show it is harmful to users. Instead, it is created more intuitively so that individuals won't know that the algorithm is compromising them unless they do an in depth look *(Sandvig et. al)*.

Appendix

Figure 1A

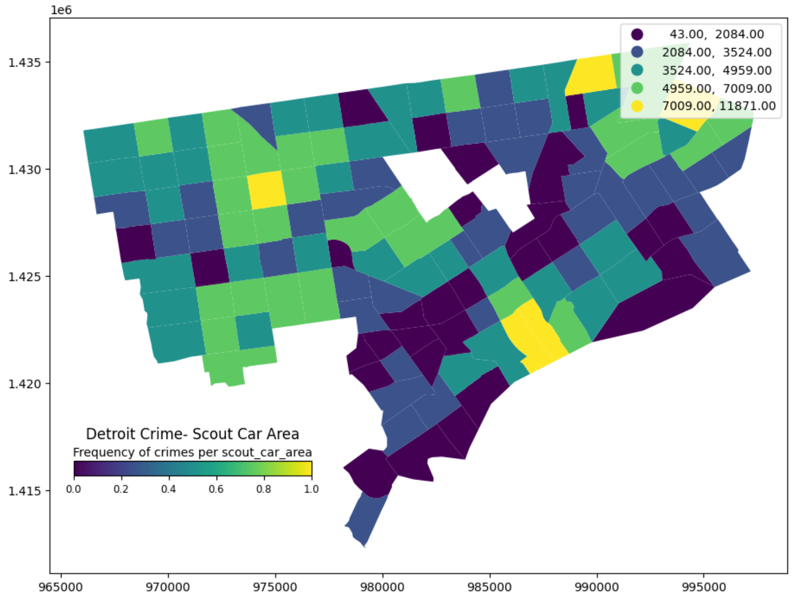

Figure 1B

```
Moran's I for relationship between crime rate and scout_car_area: 0.1116457434538516
Moran's p-value (under normality assumption) for relationship between crime rate and scout_car_area: 0.0000000126629711161
```

Figure 2A

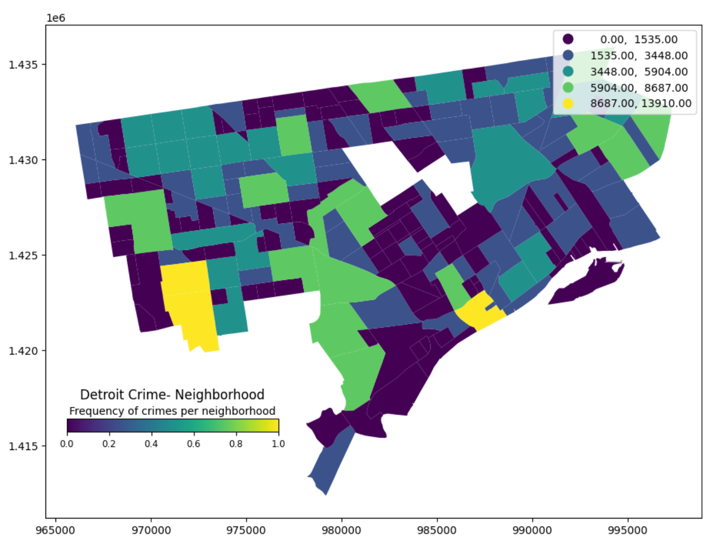

Figure 2B

```
Moran's I for relationship between crime rate and neighborhoods: 0.04688727373214758
Moran's p-value (under normality assumption) for relationship between crime rate and neighborhood: 0.0030242372509110549
```

Figure 3A

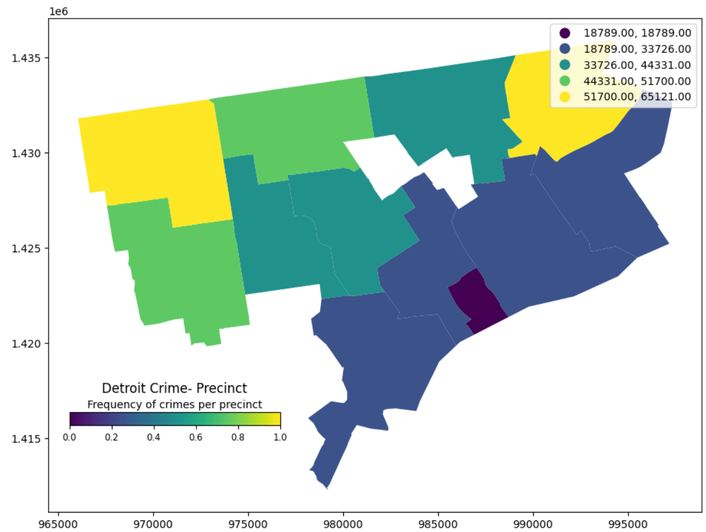

Figure 3B

```
Moran's I for relationship between crime rate and precincts: -0.0909090909090909
Moran's p-value (under normality assumption) for relationship between crime rate and precinct: 0.9999999940552968258
```

Figure 4

```
Moran's I for homes: 0.14390305379234442
Moran's p-value (under normality assumption) for homes: 0.0000000000000000000
```

Figure 5

OLS Regression Results

Dep. Variable:	homes	R-squared:	0.912
Model:	OLS	Adj. R-squared:	0.912
Method:	Least Squares	F-statistic:	1.323e+04
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	0.00
Time:	19:22:49	Log-Likelihood:	-3.7606e+06
No. Observations:	492711	AIC:	7.522e+06
Df Residuals:	492325	BIC:	7.526e+06
Df Model:	385		
Covariance Type:	nonrobust		

Figure 6

OLS Regression Results			
Dep. Variable:	hour_of_day	R-squared:	0.005
Model:	OLS	Adj. R-squared:	0.004
Method:	Least Squares	F-statistic:	6.664
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	6.00e-317
Time:	19:23:25	Log-Likelihood:	-1.6930e+06
No. Observations:	492711	AIC:	3.387e+06
Df Residuals:	492325	BIC:	3.391e+06
Df Model:	385		
Covariance Type:	nonrobust		

Figure 7

OLS Regression Results			
Dep. Variable:	day_of_week	R-squared:	0.004
Model:	OLS	Adj. R-squared:	0.003
Method:	Least Squares	F-statistic:	5.360
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	1.94e-226
Time:	19:23:58	Log-Likelihood:	-1.0390e+06
No. Observations:	492711	AIC:	2.079e+06
Df Residuals:	492325	BIC:	2.083e+06
Df Model:	385		
Covariance Type:	nonrobust		

Figure 8

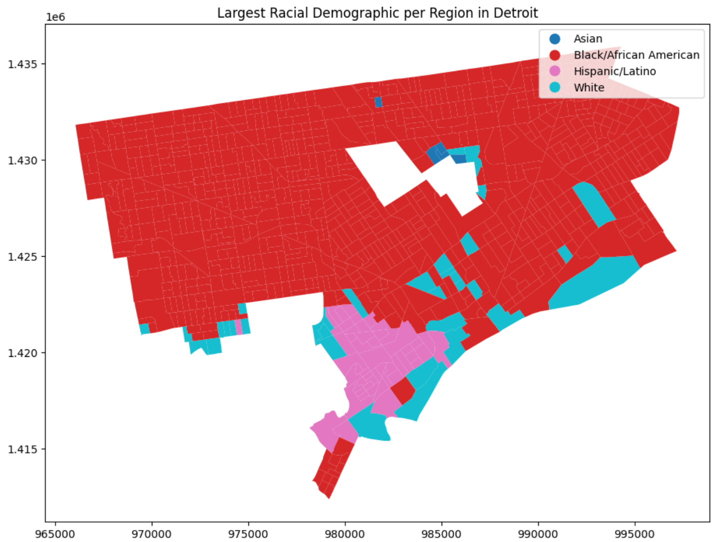

Figure 9

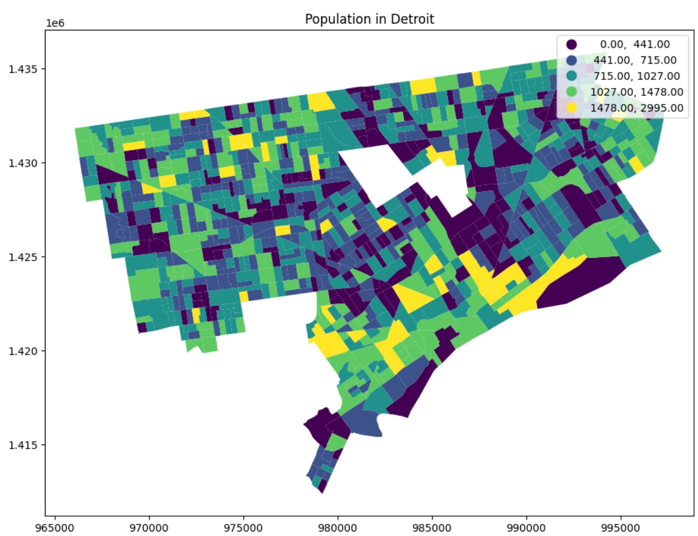

Figure 10

OLS Regression Results

Dep. Variable:	Crime_Count	R-squared:	0.927
Model:	OLS	Adj. R-squared:	0.922
Method:	Least Squares	F-statistic:	182.0
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	2.16e-39
Time:	19:24:11	Log-Likelihood:	-794.83
No. Observations:	78	AIC:	1602.
Df Residuals:	72	BIC:	1616.
Df Model:	5		
Covariance Type:	nonrobust		

Figure 11

OLS Regression Results

Dep. Variable:	Crime_Count	R-squared:	0.757
Model:	OLS	Adj. R-squared:	0.754
Method:	Least Squares	F-statistic:	236.4
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	4.90e-25
Time:	21:46:17	Log-Likelihood:	-841.60
No. Observations:	78	AIC:	1687.
Df Residuals:	76	BIC:	1692.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	2913.0291	1713.864	1.700	0.093	-500.426	6326.485
AA_Count	0.0015	9.74e-05	15.376	0.000	0.001	0.002

Omnibus:	71.196	Durbin-Watson:	1.793
Prob(Omnibus):	0.000	Jarque-Bera (JB):	471.573
Skew:	2.829	Prob(JB):	3.97e-103
Kurtosis:	13.634	Cond. No.	2.24e+07

Figure 12

OLS Regression Results

Dep. Variable:	Crime_Count	R-squared:	0.262
Model:	OLS	Adj. R-squared:	0.252
Method:	Least Squares	F-statistic:	26.92
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	1.71e-06
Time:	21:46:40	Log-Likelihood:	-884.91
No. Observations:	78	AIC:	1774.
Df Residuals:	76	BIC:	1779.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.486e+04	2491.755	5.964	0.000	9897.839	1.98e+04
White_Count	0.0030	0.001	5.188	0.000	0.002	0.004

Omnibus:	24.143	Durbin-Watson:	1.934
Prob(Omnibus):	0.000	Jarque-Bera (JB):	33.378
Skew:	1.387	Prob(JB):	5.65e-08
Kurtosis:	4.603	Cond. No.	4.63e+06

Figure 13

OLS Regression Results

Dep. Variable:	Crime_Count	R-squared:	0.016
Model:	OLS	Adj. R-squared:	0.003
Method:	Least Squares	F-statistic:	1.267
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	0.264
Time:	21:47:00	Log-Likelihood:	-896.09
No. Observations:	78	AIC:	1796.
Df Residuals:	76	BIC:	1801.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.835e+04	2813.624	6.523	0.000	1.27e+04	2.4e+04
Asian_Count	0.0063	0.006	1.126	0.264	-0.005	0.018

Omnibus:	39.839	Durbin-Watson:	1.812
Prob(Omnibus):	0.000	Jarque-Bera (JB):	93.461
Skew:	1.801	Prob(JB):	5.07e-21
Kurtosis:	6.972	Cond. No.	5.20e+05

Figure 14

OLS Regression Results

Dep. Variable:	Crime_Count	R-squared:	0.147
Model:	OLS	Adj. R-squared:	0.136
Method:	Least Squares	F-statistic:	13.14
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	0.000520
Time:	21:47:13	Log-Likelihood:	-890.51
No. Observations:	78	AIC:	1785.
Df Residuals:	76	BIC:	1790.
Df Model:	1		
Covariance Type:	nonrobust		

	coef	std err	t	P>|t|	[0.025	0.975]
Intercept	1.691e+04	2600.273	6.501	0.000	1.17e+04	2.21e+04
Hispanic_Count	0.0011	0.000	3.625	0.001	0.001	0.002

Omnibus:	46.011	Durbin-Watson:	1.746
Prob(Omnibus):	0.000	Jarque-Bera (JB):	129.852
Skew:	2.003	Prob(JB):	6.35e-29
Kurtosis:	7.890	Cond. No.	8.60e+06

Figure 15

OLS Regression Results			
Dep. Variable:	AA_Count	R-squared:	0.073
Model:	OLS	Adj. R-squared:	0.035
Method:	Least Squares	F-statistic:	1.937
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	0.131
Time:	19:24:11	Log-Likelihood:	-1390.2
No. Observations:	78	AIC:	2788.
Df Residuals:	74	BIC:	2798.
Df Model:	3		
Covariance Type:	nonrobust		

Figure 16

OLS Regression Results			
Dep. Variable:	White_Count	R-squared:	0.596
Model:	OLS	Adj. R-squared:	0.580
Method:	Least Squares	F-statistic:	36.45
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	1.42e-14
Time:	19:24:11	Log-Likelihood:	-1263.1
No. Observations:	78	AIC:	2534.
Df Residuals:	74	BIC:	2544.
Df Model:	3		
Covariance Type:	nonrobust		

Figure 17

OLS Regression Results			
Dep. Variable:	Hispanic_Count	R-squared:	0.544
Model:	OLS	Adj. R-squared:	0.526
Method:	Least Squares	F-statistic:	29.45
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	1.23e-12
Time:	19:24:11	Log-Likelihood:	-1320.7
No. Observations:	78	AIC:	2649.
Df Residuals:	74	BIC:	2659.
Df Model:	3		
Covariance Type:	nonrobust		

Figure 18

OLS Regression Results			
Dep. Variable:	Asian_Count	R-squared:	0.164
Model:	OLS	Adj. R-squared:	0.130
Method:	Least Squares	F-statistic:	4.841
Date:	Tue, 04 Apr 2023	Prob (F-statistic):	0.00394
Time:	19:24:12	Log-Likelihood:	-1124.3
No. Observations:	78	AIC:	2257.
Df Residuals:	74	BIC:	2266.
Df Model:	3		
Covariance Type:	nonrobust		

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