INF2178

Dissecting Police Actions on Different Demographics

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Introduction

Police brutality has become a critical issue in modern times, with its impact being felt worldwide. Despite the advancement of first world countries, including Canada, in healthcare and education, there still exists a history of treating minorities and indigenous people poorly and unfairly. The issue of police brutality is often intertwined with racism, biases towards people living in poverty, and gender inequality, with black and indigenous people being the most affected. According to a report by CBC News, indigenous people make up only 5% of the population in Canada, yet they account for 30% of the country's incarcerated population. Similarly, black people are three times more likely to be killed by police officers than white people in Canada. These statistics highlight the need for further investigation into the relationship between police brutality and racism in Canada.

One area that requires scrutiny is the arrest process and how it is influenced by race and gender. Strip searches, for example, are considered one of the most intrusive and invasive arrest methods. There have been reports of strip searches being conducted on individuals who pose no threat, and this often leads to emotional and psychological trauma. A study conducted by the Journal of Ethnicity in Criminal Justice found that black people were more likely to be strip-searched than their white counterparts during arrests for similar reasons. Furthermore, women are more likely to experience sexual assault during strip searches than men. These findings indicate a need for reforms in police procedures to eliminate racial and gender biases.

Literature Review

As seen in previous cycles of political relationship with issues upon race, crime and drugs. From a historical perspective, the relationship between race and policing has been fraught with tension and controversy. In the United States, for instance, police brutality towards African Americans has been a longstanding issue, as evidenced by high-profile cases such as the murder of George Floyd in Minneapolis. Similar patterns of police misconduct have also been observed in Canada, where indigenous people have been the target of systemic racism and discrimination. Recent research by the Ontario Human Rights Commission (OHRC) found that indigenous people are overrepresented in the criminal justice system and are more likely to be victims of police brutality.

Police misconduct towards individuals with mental health conditions has also been a growing concern in recent years. A study by the Mental Health Commission of Canada found that individuals with mental health conditions are more likely to be arrested, detained, and subjected to use of force by police officers. The study also revealed that individuals with mental health conditions are less likely to receive appropriate healthcare and support services, leading to a cycle of criminalization and victimization.

In addition to police brutality, there is also evidence of racial profiling and discriminatory practices in law enforcement. A study by the Toronto Star found that black people in Toronto are 20 times more likely to be shot and killed by police than white people. Similarly, a report by the Canadian Civil Liberties Association revealed that indigenous women are overrepresented in the Canadian prison system and are more likely to be subjected to strip searches, which can be traumatic and degrading.

Different governments implement different policies in the power of police and what they can do. From historical standpoints, we see that there is an increase in police brutalities towards individuals with reliance on substances and alcohol. Additionally, we see individuals with higher education levels or a better professional job. While focusing into the country of Canada, Research sampled 16,000 Candians and found out that around 23% of Canadians was a victim of discrimination. With the most reports being racial discrimination. However, it is interesting to note that the data collected from the research mentioned is predominantly white, the white population in the dataset is near 80%, while the White population in Toronto is around 40~45%. The researcher also pointed out that White people are significantly less likely to endure racial based discrimination or in fact any discrimination overall. Female also endure more gender based discrimination and that income discrimination. We also observe that there is a higher amount of discrimination in the younger generation than those who are more aged.

EDA

Dataset Description

Our dataset is collected by the Toronto Police department that documents the Arrests, Booking and Strip Search conducted by police officers upon individuals from different social-demographic backgrounds carried on between the year 2020 & 2021. Describing the dataset, there is “Arrest_Year” and “Arrest_Month” which specifies the period of which the individual is arrested. There are three Identification Numbers, firstly the EventID is where the Identification number of the arrest. In our assumption ArrestID is most likely the identification number of the police officer. Furthermore in our assumption, PersonID is the identification number of the individuals being arrested. The assumption is based on mostly matching social demographic background following the identical PersonID. Following the identification numbers, there exhibits social demographic backgrounds such as “Perceived_Race” stating the racial background of the arrestee (White, Black, Indigenous, South Asian, East & South East Asian, Middle Eastern, Latino or Unknown & Legacy). Following is two age indicators, one is

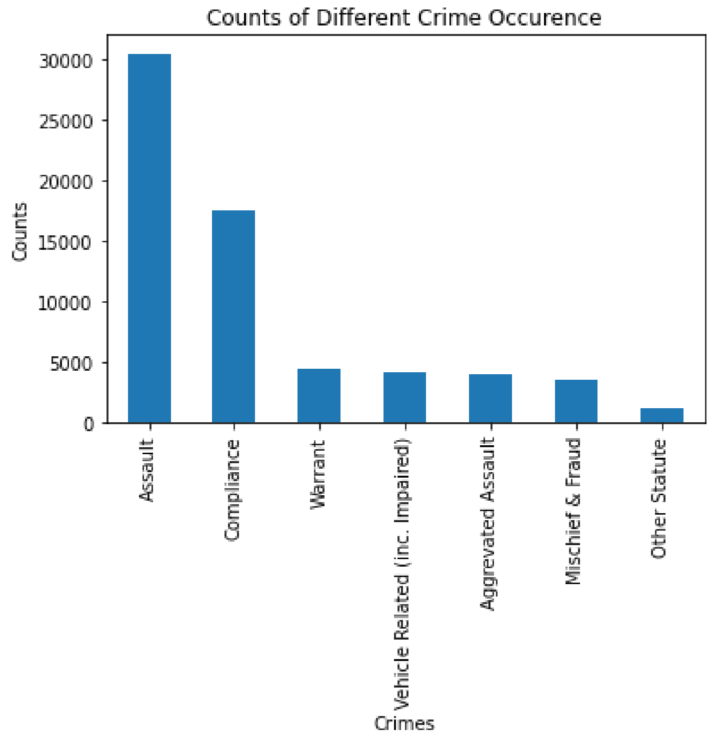
“Age_group__at_arrest_” and another is “Youth_at_arrest__under_18_years” categorizing arrestees into different age level and whether they are a youth or not. “ArrestLocDiv” is a column stating the location of the division that made the arrest, if the location is in an exterior jurisdiction, it will be marked with a XX. The columns “StripSearch” and “Booked” records further steps taken after the arrest, it is important to note that while the dataset does not show, if Strip Search happened, a booking took place. Some areas of the data set have a 1 for Strip Search and 0 for Booked, which is incorrect. The column “Occurrence_Category” indicates why the arrest occurred, ranging from assault, warrant, fraud to murder. The following columns are related towards the actions the individuals took after being arrested, most are aggressive stances with one cooperative option. Then it gave the officer columns to record why did perform the search and if there were any items found.

Data Cleaning

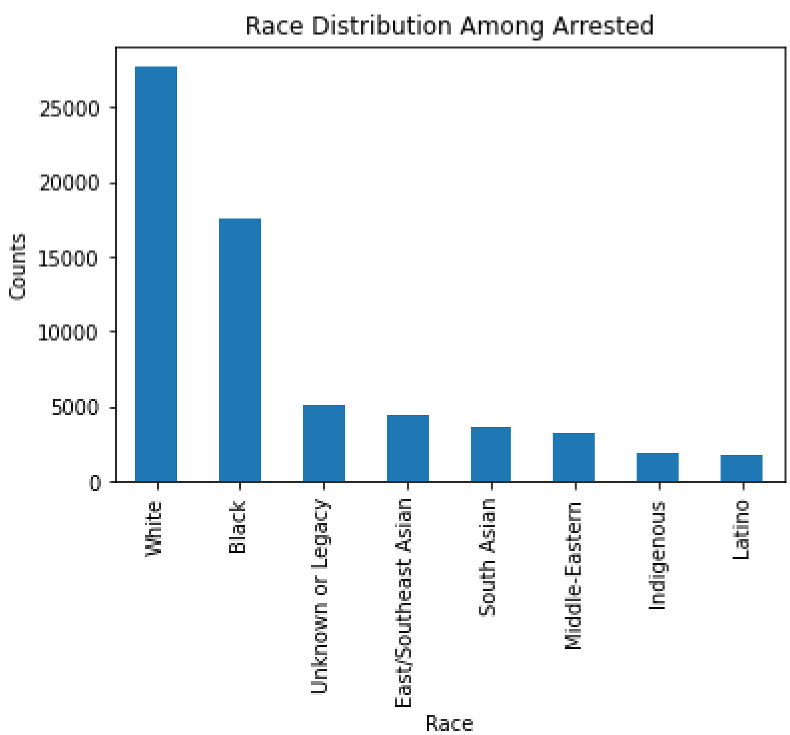
Our focus of the research paper is centered around the amount of arrests and the amount of strip searches conducted on different gender, race and crime occurrence category. Thus we can lighten the load of the calculation by dismissing the unneeded columns from the dataframe. Thus we filter out the columns “Arrest_Year” , “Arrest_Month” , 'EventID', 'ArrestLocDiv', 'Actions_at_arrest___Concealed_i', 'Actions_at_arrest___Combative__', 'Actions_at_arrest___Resisted__d', 'Actions_at_arrest___Mental_inst', 'Actions_at_arrest___Assaulted_o', 'Actions_at_arrest___Cooperative', 'ItemsFound', 'ObjectId'. After initial diving into the dataset, we observe that there are 9 individuals with genders categorized as U, we decided to remove those observations since they will skew our dataset and it can be considered as outliers. After that, I decided to reorganize the occurrence category into seven main categories. The seven main categories are Assault, Aggravated Assault, Vehicle related, Compliance, Mischief and Fraud, Warrant and Other Statue. We also recode some age entries as officers sometimes type in Age and Aged differently or younger and under differently.

Descriptive Statistics

As part of our initial findings, we want to look at some of the distribution of the factors we are interested in. Firstly, after our initial data cleaning, we created an output that shows the amount of counts different crime categories have occurred. We observed that the highest number of crime categories is Assault, followed by more lenient Compliance, Warrant and Vehicles. Then it is followed by the most violent category Aggravated Assault, then Mischief & Fraud. Finally, it is Other Statue, which has the lowest amount of counts and is not necessarily a crime. As it may be health or danger related.



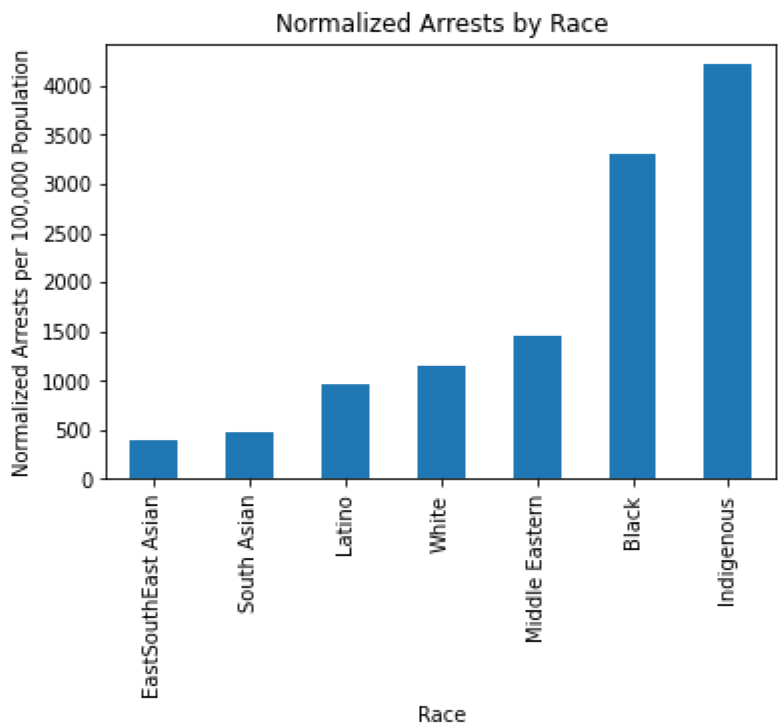
Moving on to the second descriptive statistics, we want to observe the amount of arrest made between different race counts. We see that there was the highest number of White individuals being arrested, followed by Black, Unknown, East Asian, South Asian, Middle-Eastern, Indigenous and finally Latino.



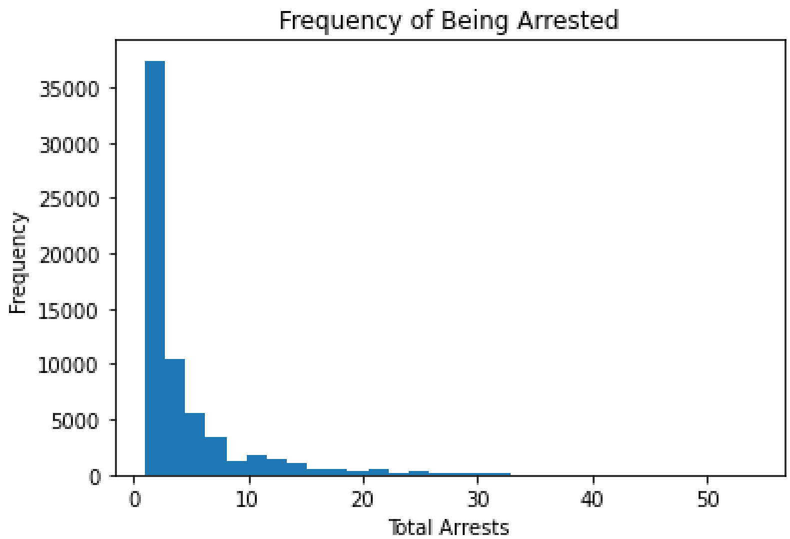
However, we need to consider the instance that the population count of different races are not identical. After incorporating the census data collected by Statistics Canada 2021, we formulate the per 100,000 arrest counts between different races.
The formula is as follows:

$$\frac{\text{Total arrest count of race x}}{\text{Total population of race x}} \times 1/100,000 \text{ people} \times \frac{1}{2} \text{ years}$$

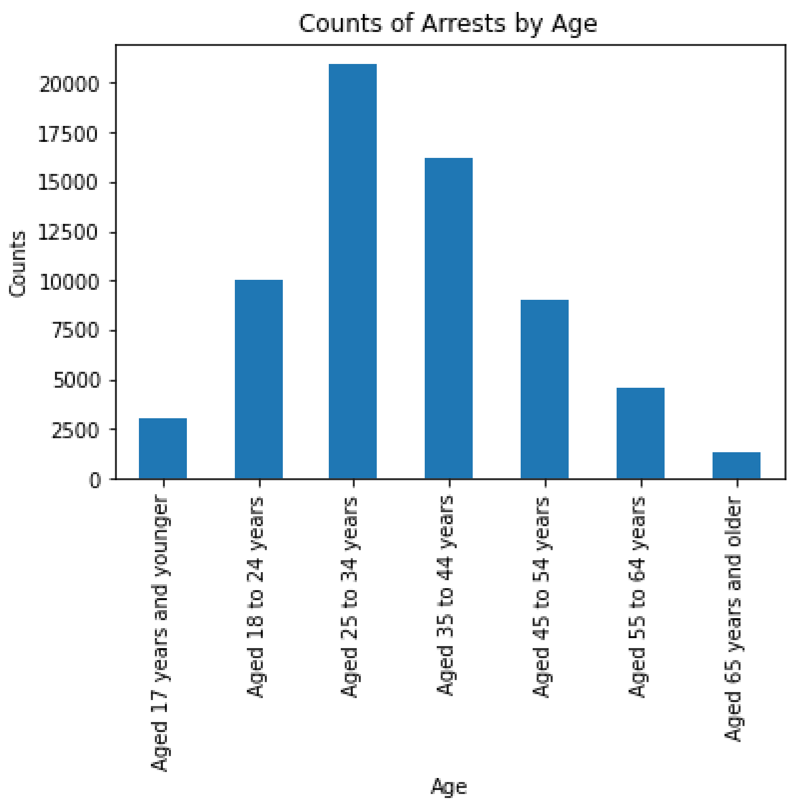
After normalizing the arrest data by population count provided by Statistics Canada, we observe that by population capita most arrests occur within the Indigenous, Black and Middle Eastern race community. Even though there are the most white arrests, if we compare the data by total population, the percentage is low. The Asian and Latino community have the lowest amount of arrest if we normalize by the local population.



After viewing the normalized data, we have a suspicion that there are biases towards arresting Indigenous and Black individuals more than other races.
We want to further investigate the amount of times each individual in the race is getting arrests. Using the PersonID identifier, we count the amount of times each PersonID is mentioned, each time a PersonID is mentioned it signifies 1 arrest, naming the column as ArrestTotal. We would have to clean the ArrestTotal column by dropping any Na or NaN columns.
We see that most individuals are only arrested once but there are definitely high amounts of individuals being arrested multiple times.



We also investigated how different age groups affect the number of arrests. After recoding the inputs, we produced a histogram documenting the arrest ages. However this data is skewed by nature as not every range exhibits the same number of ages, some contain less years.



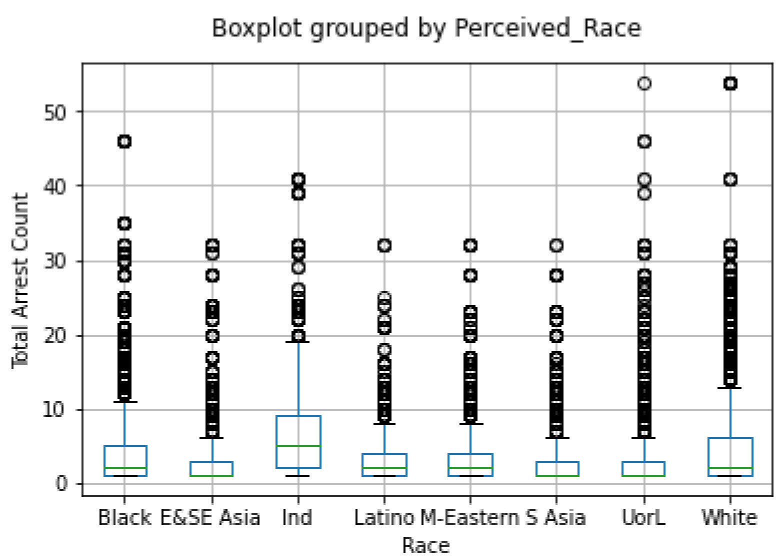
Before we proceed into conducting two sample t tests or two way anova tests, we want to first perform Normality checks on the dependent variables that we are interested in investigating.

Assumption Checking
Using the Anderson Darling Test we determined that the dependent variable TotalArrest is not normal since it fails to pass. The statistics derived from the test is greater than all quantiles of a normal dataset, thus the dependent variable TotalArrest is not normal.
We then move on to the other factor we want to analyze, Strip Search. To investigate who police strip searches most often we create a new dataframe that includes all individuals that have been Strip Searched. Then using the sum function to calculate the sum of the times they have been strip searched. Furthermore, we keep Perceived race and Occurrence categories and transfer them into the new dataframe. Similar to above we observe that the data is not normal as it does not pass the Anderson Darling test.
Both data we have used in the dataset is too skewed to be considered normal.

Two Sample T Tests
Our first two sample T Tests investigates the difference between the amount of times individuals from each race are arrested. We first picked out the race White and Indigenous to conduct the Levene equal variance test as a part of our assumption check. However, the data set failed the equal variance test.
We moved on to the two sample t-tests while signaling that the samples are not of equal variance. Our result is shown in the following table, suggesting that there is a statistically significant difference in the two samples.

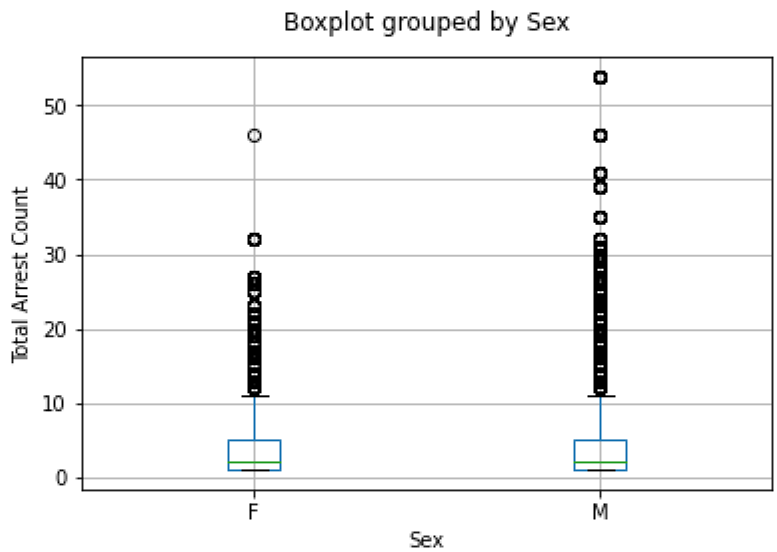
T Statistic	-15.42
P Value	7.54 * e^-51

We then formulate a boxplot of every race to view.



Our second two sample t tests feature Sex and Total Arrests. Similar to above, we first conducted the Levene test to see if there exhibit equal variance between Male and Female population. The sample still does not pass the equal variance test. Using the two samples to test upon the data, we see that they still exhibit statistically significant differences between Male and Female arrests.

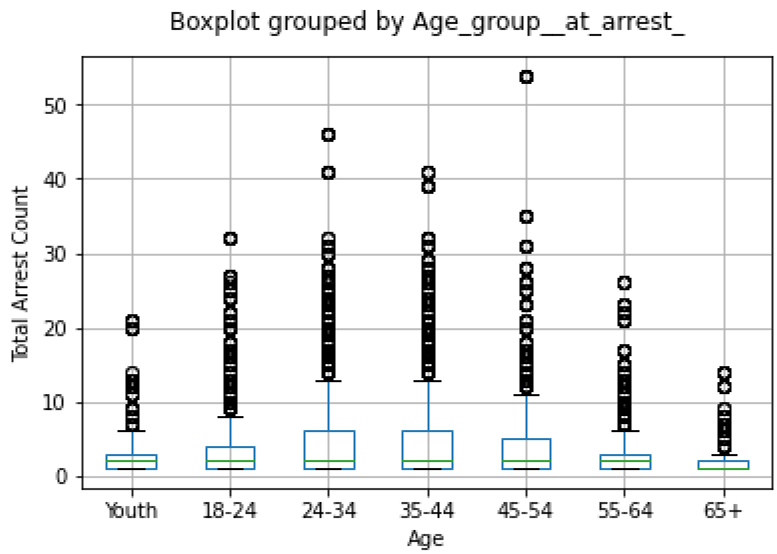
T Statistic	5.51
P Value	3.56 * e^-8



Our third T Test features different age levels. We first picked out two age ranges, age 25-34 and age 35-44. Conducting the Levene equal variance test, we see that equal variance exists among the two samples. Thus we will be conducting the two sample t tests with equal var equalling True. We observe that there is a statistically significant evidence that age group affects the counts for Total Arrests.

T Statistic	-2.72
P Value	0.0065

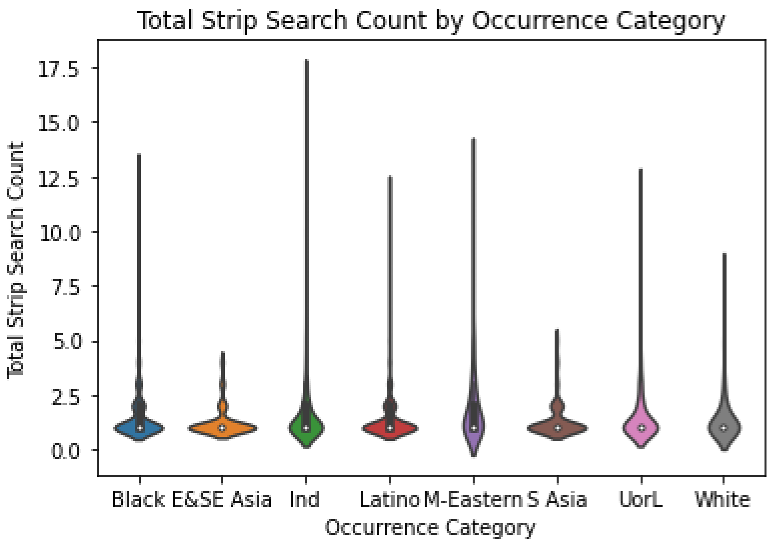
We created a box plot to visualize the amount of total arrests that happen in different age groups. We see that there are more arrested between 25-44 years old range.



Our fourth two sample t tests feature the amount of times each individual in different races gets Strip Searched. Using the race mentioned above, we selected White and Indigenous people. Similarly as above, we first conducted an Levene equal variance test, however, the data did not pass the equal variance test. We then conducted the two sample t tests and reached the results below. The p value suggests that there is a statistically significant difference in the strip search times between the two races.

T Statistic	-2.23
P Value	0.027

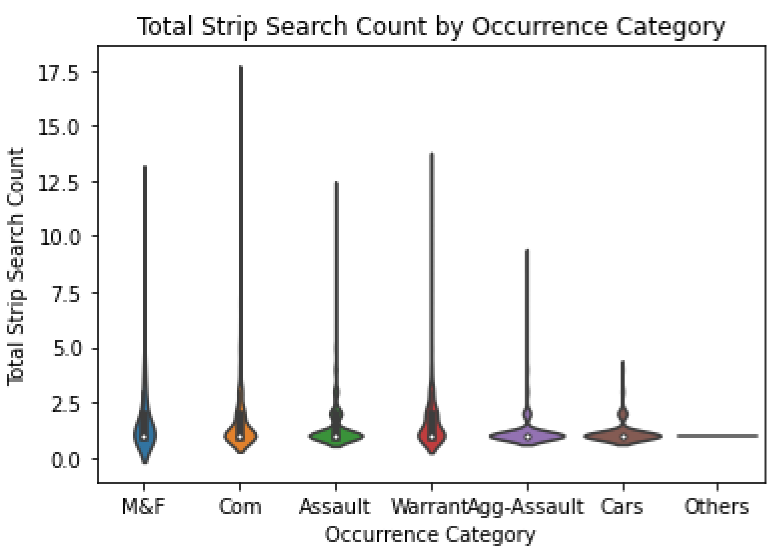
To better visualize the data, we created a violin plot to observe the difference in total strip search counts between different races. We see that there are several outlier individuals. One Indigenous man was strip searched 17 times in two years!



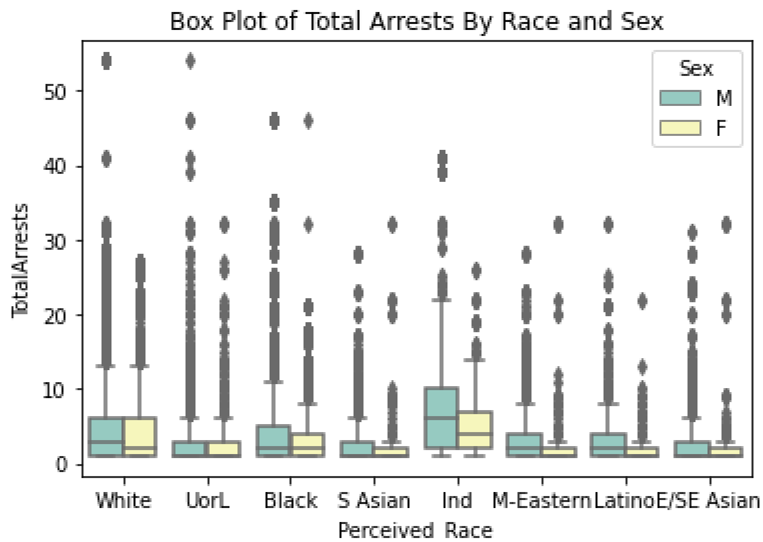
Moving on to our final two samples t-test five. Our final t test wants to investigate how different occurrence categories affect the likelihood of having a strip search. Using the Levene's equal variance test, there is no equal variance exhibit in the sample. The two sample t-tests generated the following table, which suggest there is a statistically significant difference in the amount of strip search conducted from different occurrence categories.

T Statistic	-3.6
P Value	0.00032

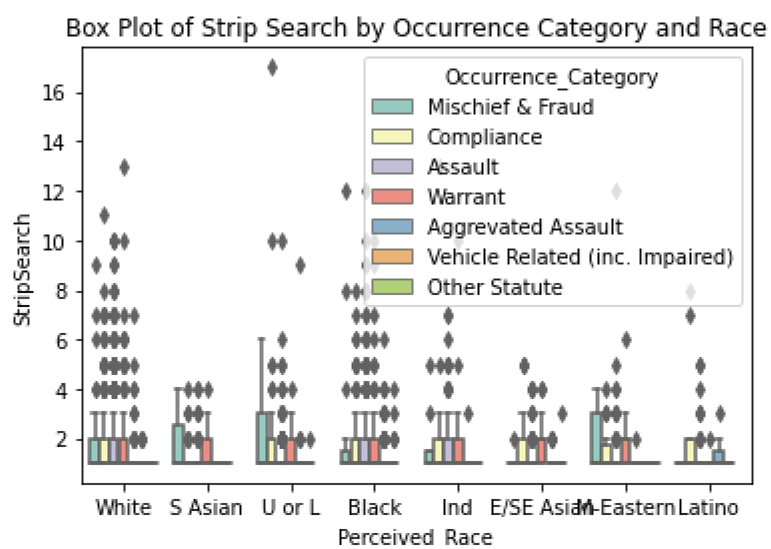
After the two sample t tests, we want to visualize the dataset by creating an visualization of the number of strip counts by occurrence category.



In preparation for the two way Anova, we produced the following boxplot which scribes the amount of arrests separated by race and sex. Similar to above, Indigenous have the higher number of total average arrests. For some races, gender are more closely distributed but for other races there is a clear difference.



For our second two way Anova, we created a table that portrays the number of Strip Search done upon different races while conducting different crime occurrence types. We observe that there may be insufficient data to cover all races since some races do not have enough record of being strip searched during a specific occurrence type. This may create some difficulties in the Anova model. However, I decided to run the model with all races included.



Anova
Research Question & Objectives
Our study will seek to examine two main research questions.
The first research question is to investigate the effects that Race and Sex have upon the amount of time an individual will be arrested. Our Null Hypothesis is that Race, Sex and the interactions between Race and Sex does not affect the amount of times one will get arrested. Our Alternative Hypothesis is that either one or both Race, Sex and their interaction will affect the number of times one will get arrested.
The second research question is to investigate the effects of Occurrence Category and Race have upon Strip Search. Our Null Hypothesis is that Occurrence Category, Race and their interactions will all have no effect upon the probability of an individual getting strip searched. Our Alternative Hypothesis is that either Race, Occurrence Category or their interaction have an effect on the probability of one getting Strip Search.
Our main research objective is to identify if biases exist in police actions, and also identify the community that is experiencing an overload of police attention.

Methods
We decided to use Two Way Anova to measure if they exhibit an effect on the independent variable we chose and/or the interaction between the two independent variables. Additionally, we decided to use an interaction plot to visualize and display our findings. Visualized data can also lead us to future steps and idea generation. Finally, to observe the changes that interaction plots create, we will use the Post Hoc method to analyze the effects of interactions.

Anova Research Question 1

We created a model for Total Arrest as follows, we locked the Sex treatment as M and Race Treatment as SouthEast Asian. So it will be easier and faster to reach and interpret our discovery.

$$TotalArrest \sim C(Sex, Treatment("M")) + C(Perceived\_Race, Treatment("East/SoutheastAsian")) + C(Perceived\_Race, Treatment("East/SoutheastAsian")) : C(Sex, Treatment("M"))$$

After running our two way anova model, we got the result as follows.

Two Way Anova TotalArrest ~ Sex + Perceived Race + Perceived Race:Sex

	sum_sq	df	F	PR(>F)
C(Sex, Treatment("M"))	2.43*e3	1	80.26	1.5e-20
C(Perceived_Race, Treatment("East/Southeast Asian"))	5.83e4	7	295.71	0
C(Perceived_Race, Treatment("East/Southeast Asian")):C(Sex, Treatment("M"))	3.47e3	7	17.57	1.9e-23
Residual	1.84e6	65427		

We observe that both treatments and their interaction have a small p-value, which suggests that they have a statistically significant effect on the dependent variable of total arrest.

Following our discovery in the difference of mean total arrest counts between different genders and races, we apply the Tukey HSD test to examine statistically significant differences between different groups of individuals. We will only be interested in regions where the reject signal equals to true, in this scenario it is rejecting the null hypothesis of no difference. We will focus more upon within-race sex discrimination and the biggest within-sex race discrimination.

Tukey HSD Total Arrest by Perceived Race and Sex

Group 1	Group 2	Mean Diff	P - Adj.	Lower	Upper	Reject
Black / F	Black / M	0.4357	0.0055	0.064	0.807	True

Black / F	SouthEast Asian/M	-0.7573	0.001	-1.21	-0.302	True
Black / M	Indigenous/F	1.61	0.001	0.86	2.37	True
SouthEast Asian/M	White/F	1.462	0.001	1.08	1.85	True
MiddleEastern /M	White/F	0.97	0.001	0.549	1.39	True
Latino/M	White/F	0.9933	0.001	0.46	1.53	True
Indigenous/F	MiddleEastern /M	-2.3095	0.001	-3.13	-1.49	True
Indigenous/F	Latino/M	-5.433	0.001	-6.13	-4.73	True
Indigenous/F	SouthAsian/M	-5.88	0.001	-6.49	-5.23	True

After running the post hoc test, we decided to extract some of the more glaring mean differences we observed. If we exclude Indigenous and Unknown and legacy entries, White M and White F are actually very likely to be arrested. As we see in the Tukey table, White/F have a higher number of arrests than Asian & Latino male. Similarly Black Female also have a higher number of mean arrests than South East Asian Male. However, the most conspicuous issue we see is the number of arrests conducted upon the Indigenous community regardless of gender as they have a really high number of arrests compared to any other gender and race groups.

Anova Research Question 2

Our second research question is to determine how race and occurrence type affect the amount of time an individual received a strip search from the police. We first create a new dataframe containing the PersonID, Perceived_Race, Occurrence_Category along with the amount of times they were Strip Searched.
We built our model from the new dataframe. The model is as follows, the dependent variable we want to investigate is StripSearch. The independent variables we want to investigate are Occurrence Category and the Perceived Race. We would also like to investigate the interaction effect between Race and Occurrence Category.
Our Null Hypothesis is that both Occurrence Category and Perceived Race along with the interaction effect between the two independent variables do not affect the times that a suspect will be Strip Searched.

Our Alternate Hypothesis is that the independent variables or the interaction effect between the two variables show statistically significant evidence that it affects the times a suspect received a strip search.

$$StripSearch \sim C(Occurrence\_Category, Treatment("Assault")) + C(Perceived\_Race, Treatment("White")) + C(Perceived\_Race, Treatment("White")) : C(Occurrence\_Category, Treatment("Assault"))$$

After running the two way anova, we discovered that both Occurrence Category and Perceived Race have a significant effect upon the Strip Search. However the interaction between Race and Occurrence category is not significant. Even though the interaction is not significant, there may still be individual pairs either between identical race or identical sex that show a significant impact.

Two Way Anova StripSearch ~ Occurrence_Category + Perceived Race + Perceived Race: Occurrence_Category

	sum_sq	df	F	PR(>F)
C(Occurrence_Category, Treatment("Assault"))	120.5	6	13.96	8.26e-16
C(Perceived_Race, Treatment("White"))	84.7	7	8.41	3.75e-3
C(Perceived_Race, Treatment("White")):C(Occurrence_Category, Treatment("Assault"))	42.7	42	0.71	9.04e-1
Residual	7186.68	4994		

Due to the high number of Occurrence Categories and Race, there is a high number of interactions. Even if most do not have a significant difference, we still want to investigate further to see if there are any race or occurrence types that have interaction effects present.

Tukey HSD Strip Search by Perceived Race and Occurrence Category

Group 1	Group 2	Mean Diff	P - Adj.	Lower	Upper	Reject
Black / Aggravated Assault	Indigenous / Assault	0.749	0.001	0.181	1.32	True

Indigenous / Assault	South Asian / Assault	-0.7219	0.0149	-1.39	-0.053	True
Indigenous / Assault	White / Aggravated Assault	-0.7151	0.0071	-1.35	-0.078	True
East/Southeast Asian / Assault	Indigenous / Assault	0.7037	0.0082	0.072	1.335	True

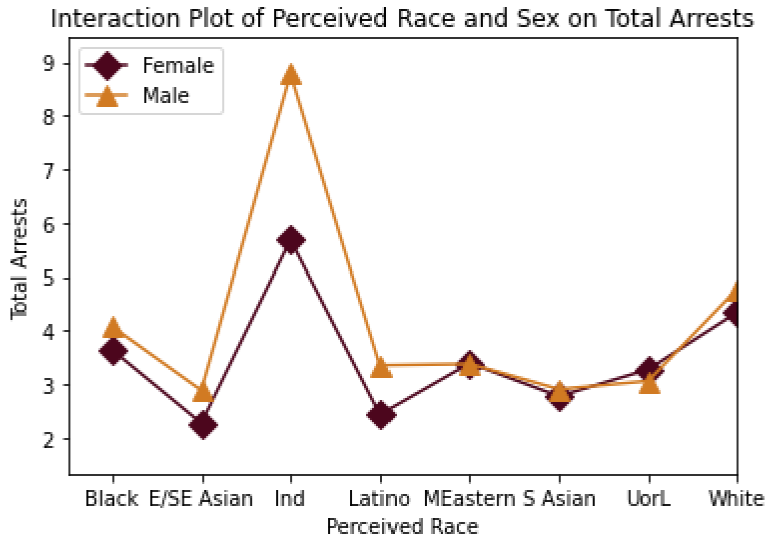
As we found in the two way anova model we ran previously, we observe that there are no significant interaction effects overall. However, we are still able to produce and retrieve a fact that there is a significant increase in strip search count in the group Indigenous / Assault. This is significant because not only does strip search count increase compared to Assault of other races, Indigenous individuals receive more strip searches due to assault than white people receive due to aggravated assaults, which has more violence included.

Results & Findings

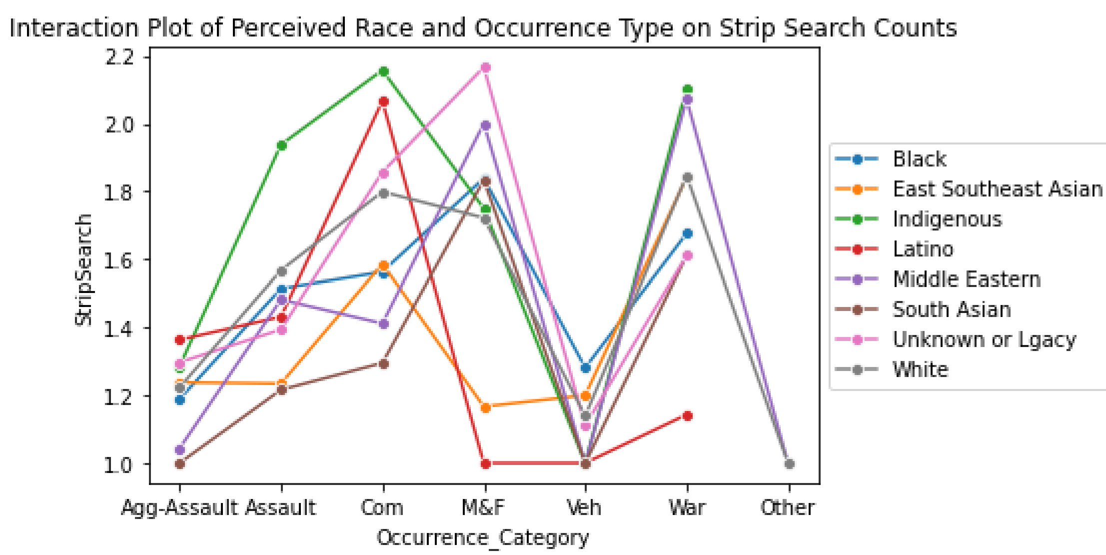
After running our two way Anova models. Using two sample t tests we took an initial visualization between the different independent variables that we would like to observe. We came to a conclusion that Race & Gender affects Total Arrest. Race & occurrence category affects the amount of mean strip search as well. We have statistically significant evidence that shows Age affects Total Arrest but not as significant, due to the p value being less than 0.05 but greater than 0.01. Thus we did not continue searching in that direction.

Using two way anova we were able to check the magnitude and significance of the different independent variables and if their interaction is significant or not. We observe that the interaction effect between Race & Gender is significant and the interaction effect between Race & Occurrence category is not. Using Post Hoc to check our findings, we drew out very significant differences between groups most specifically in the Indigenous community, individuals are getting both arrested and strip searched more than any other race regardless of gender. We also drew out significant findings in the Race & Occurrence model, which shows that Indigenous charged with Assault having extra Strip Search counts than other crimes and races if we examine as grouped data. Additionally, most data points towards excessive police action taken towards Indigenous individuals followed by White and Black individuals.

We created an interaction plot for Race and Sex on the dependent variables Total Arrests. The plot shows several surprising and insightful knowledge. We observe that generally male have a higher total arrest count. The largest difference between Male and Female occurs in the Indigenous community. However, Indigenous women have a higher arrest count than average individuals in other races as well.



To better analyze our model, we will create an interaction plot to visualize the data. Below is the interaction plot for the stripsearches conducted on different races between different occurrence categories. We observe that these races have different strip search attempts between different occurrence types. Indigenous people, for example, have the highest Strip Search rate due to Assault, Compliance and Warrant while Latino have the highest count of strip search with Aggravated Assault and Black people have the highest mean strip search count while being pulled over.



We come to some valuable conclusions generated from our dataset collected by the Toronto Police Department. Our first insight is that the total arrest count is affected by both independent variables Race and Gender along with the interaction between the two variables. Our second insight is that Strip Search counts are affected by the both independent variables Race and Occurrence Category but not the interaction between the two variables. However, we observe a high rejection rate from our Tukey HSD test if one of our groups is Indigenous/Assaults.

Limitations

We ran into several limitations in this assignment, some are rather solved but others are not. Firstly, the dataset that we are presented with was not normal. This is half-solved due to the dataset being a big dataset with tens of thousands of observations. Applying the central limit theorem upon two way Anova is still an acceptable route. Our second limitation is that compliance checks, parrolle checks and mental health checks are not necessary “arrests”. Although they do not make a big impact upon the dataset overall, it may still skew the data of some observations. Our third and fourth limitation occurred from the Occurrence Category. The third limitation is derived from the low number of Strip Search or Arrest by aggravated assault, in my opinion, this is due to individuals being further detained or enjailed after being arrested for aggravated assault. Thus it skews our observation of the data. We do not have a good response to this so we would take data received from Aggravated Assault with an extra grain of salt. Our fourth limitation is that Occurrence Category in the dataframe we created are used by the first observation, which suggests that, for example if a personID 399999 committed Assault first, then his further observations will be all assaults. This is a rather important issue that would heavily skew the data. However, I am limited in terms of finding and creating a better dataframe and that a load of it is explainable. Further arrests or police checks are related to the first offence and some individuals are recurring thiefs or fraudsters. Our fifth limitation occurs when the officers load data into the system, they fill in Unknown or Legacy. With preliminary data observations, unknown or legacy are usually minorities, however it is not certain which minorities group. Thus we need to not want to trust comparisons with the Unknown or Legacy Racial group. Finally, some social-demographic backgrounds are interchanging, some individuals are recorded as different races or gender in different arrests. This is solved partially by keeping the first entry as the base case scenario.

Conclusion

Using the police arrest and strip search dataset we are trying to observe the racial and gender bias from officer actions. We observe excessive StripSearch and Arrests in the Indigenous community. We also observe that there are more actions taken on the Black and White communities as well.

Discussion

There are several steps that we can take for relative studies in the future. The first step is to create a better database system for the Police or other public authorities to maintain and monitor their data. The second step is to curate studies and datasets that are more specific to the population of interest, the Indigenous community. We want to discover why individuals in the community are more likely to fall under the pressure of police and how we can manage to reshape their communities. Within the dataset, we can incur other studies as well, such as location based, or officer based.

References & Citation
APA

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