Final Project

August 12, 2023

1 Theft in West Point Grey and Dunbar-Southlands

Group 34: Andy Hu, Wendi Ke, CC Liang, and Mridul Manas

Source: https://raw.githubusercontent.com/fankayii/STAT201_34/main/images/theft.jpg

2 1. Introduction

Crime brings chills down everyone's spines, with theft being the most common type of crime in Canada (Government of Canada). Section 322 of the Canadian Criminal Code defines "theft" as "fraudulently and without colour of right" taking someone's property or converting its ownership (Criminal Code). Understanding crime statistics is crucial to enhancing community relations, measuring prevention initiatives, and minimizing risks by making better decisions (Vancouver Police Department). In this paper, we will study the proportion of theft crime in Dunbar-Southlands and West Point Grey, the two neighbourhoods closest to the University of British Columbia Vancouver campus (UBC Vantage College).

2.0.1 Research Question

Is the proportion of theft occurring in the neighbourhood of West Point Grey higher than Dunbar-Southlands?

2.0.2 Variables

The random variable of interest for comparison is the proportion of theft in Dunbar-Southlands and West Point Grey. For the response variable, difference in proportions is the location parameter and standard error is the scale parameter.

2.0.3 Hypotheses

- Null Hypothesis H_0: There is no difference between the proportion of theft in the neighbourhoods of Dunbar-Southlands and West Point Grey.
- Alternative Hypothesis H_A: The proportion of theft in West Point Grey is higher than in Dunbar-Southlands.

Null Hypothesis H_0	Alternate Hypothesis H_A
$H_0 : p_w - p_d = 0$	$H_A : p_w - p_d > 0$

2.0.4 Dataset Description

To conduct our research, we use the Vancouver Police Department (VPD) crime data, which includes information on the different types of crimes in Vancouver from 2003 to 2023. We will be focusing on crimes within the last 5 complete years, 2018 to 2022, in West Point Grey and Dunbar-Southlands to base our research upon more recent and contemporary crimes.

3 2. Methods and Results

3.0.1 Exploratory Data Analysis

The `tidyverse`, `infer`, and `broom` packages allow us to clean and wrangle data, create visualizations, and make statistical inferences.

[1]:
```
library(tidyverse)
library(infer)
library(broom)

options(repr.plot.width = 10, repr.plot.height = 6)
```

```
  Attaching packages                                tidyverse
1.3.2
 ggplot2 3.3.6          purrr   0.3.4
 tibble  3.1.8          dplyr   1.0.10
 tidyr   1.2.1          stringr 1.4.1
 readr   2.1.2          forcats 0.5.2
  Conflicts
tidyverse_conflicts()
 dplyr::filter() masks stats::filter()
 dplyr::lag()    masks stats::lag()
```

Since we uploaded the dataset to our GitHub repository, we can read the csv file from our GitHub link.

[2]:
```
crime <- read.csv("https://raw.githubusercontent.com/fankayii/STAT201_34/main/
 ↪data/crime.csv")
head(crime)
```

A data.frame: 6 × 10

	TYPE	YEAR	MONTH	DAY	HOUR	MINUTE	HUNDRED_B
	<chr>	<int>	<int>	<int>	<int>	<int>	<chr>
1	Theft from Vehicle	2008	12	7	18	0	11XX E HAST
2	Theft from Vehicle	2009	8	28	19	0	11XX E HAST
3	Theft from Vehicle	2012	7	25	12	0	11XX E HAST
4	Theft from Vehicle	2014	5	8	12	49	11XX E HAST
5	Theft from Vehicle	2014	10	19	18	0	11XX E HAST
6	Theft from Vehicle	2015	2	18	18	30	11XX E HAST

First, we check for any NA values in our dataset.

[3]:
```r
print(sum(is.na(crime)))
head(crime[!complete.cases(crime), ])
```

```
[1] 146
```

A data.frame: 6 × 10

	TYPE <chr>	YEAR <int>	MONTH <int>	DAY <int>
310264	Vehicle Collision or Pedestrian Struck (with Injury)	2003	6	22
311248	Vehicle Collision or Pedestrian Struck (with Injury)	2004	11	7
311366	Vehicle Collision or Pedestrian Struck (with Injury)	2003	9	20
311484	Vehicle Collision or Pedestrian Struck (with Injury)	2003	8	31
311596	Vehicle Collision or Pedestrian Struck (with Injury)	2004	10	5
311649	Vehicle Collision or Pedestrian Struck (with Injury)	2003	5	30

We demonstrated removing the 164 NA values from X and Y below, but we decide to ignore them since they don't affect the neighbourhood and type columns, and only the X and Y longitudinal and latitudinal positions of the crimes.

[4]:
```r
na.omit(crime) %>%
    head()
```

A data.frame: 6 × 10

	TYPE <chr>	YEAR <int>	MONTH <int>	DAY <int>	HOUR <int>	MINUTE <int>	HUNDRED_E <chr>
1	Theft from Vehicle	2008	12	7	18	0	11XX E HAST
2	Theft from Vehicle	2009	8	28	19	0	11XX E HAST
3	Theft from Vehicle	2012	7	25	12	0	11XX E HAST
4	Theft from Vehicle	2014	5	8	12	49	11XX E HAST
5	Theft from Vehicle	2014	10	19	18	0	11XX E HAST
6	Theft from Vehicle	2015	2	18	18	30	11XX E HAST

Next, we filter for our years of interest.

[5]:
```r
crime_overall_recent <- crime %>%
    filter(YEAR >= 2018 & YEAR <= 2022) %>%
    select(TYPE, NEIGHBOURHOOD)

colnames(crime_overall_recent) <- c('type', 'neighbourhood')
head(crime_overall_recent)
```

A data.frame: 6 × 2

	type <chr>	neighbourhood <chr>
1	Theft from Vehicle	Strathcona
2	Theft from Vehicle	Strathcona
3	Theft from Vehicle	Strathcona
4	Theft from Vehicle	Strathcona
5	Theft from Vehicle	Strathcona
6	Theft from Vehicle	Strathcona

To study theft crime proportions, we will group all the different types of crime into exclusively one of `theft` or `not theft`.

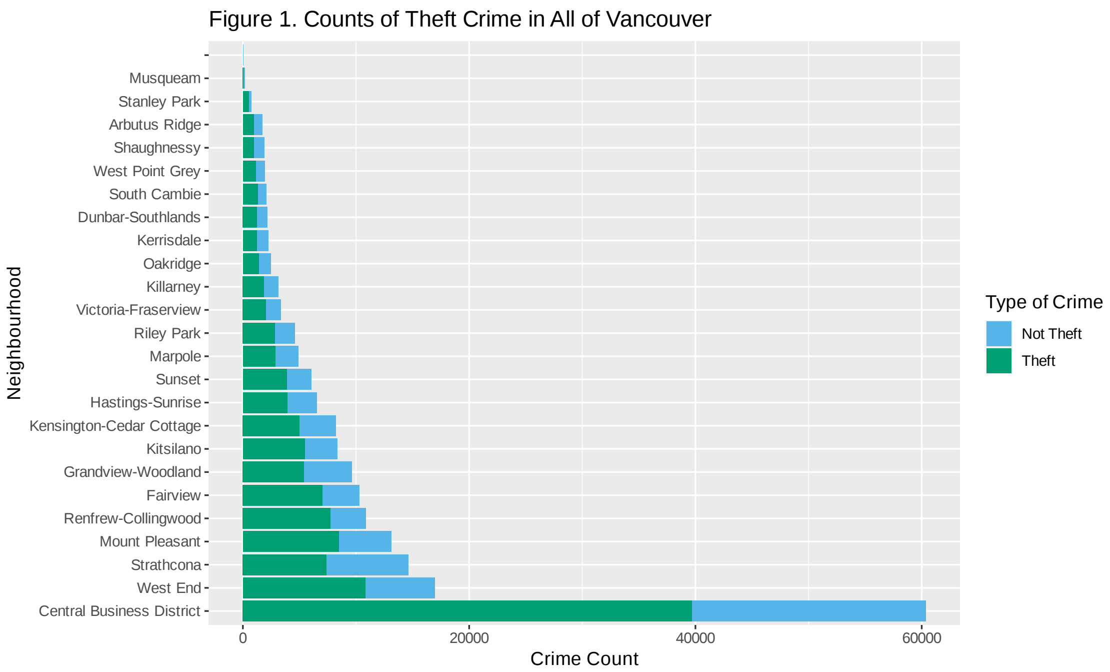
[6]:
```
crime_overall <- crime_overall_recent %>%
    mutate(type = case_when(
    type %in% c("Other Theft", "Theft from Vehicle", "Theft of Bicycle", "Theft␣
↪of Vehicle") ~ "theft",
    TRUE ~ "not_theft"))

head(crime_overall)
```

A data.frame: 6 × 2

	type	neighbourhood
	<chr>	<chr>
1	theft	Strathcona
2	theft	Strathcona
3	theft	Strathcona
4	theft	Strathcona
5	theft	Strathcona
6	theft	Strathcona

Let us visualize all our theft data below.

[7]:
```
ggplot(crime_overall, aes(y = reorder(neighbourhood,␣
↪-table(neighbourhood)[neighbourhood]), fill = type)) +
    geom_bar() +
    labs(x = "Crime Count",
         y = "Neighbourhood",
         fill = "Type of Crime",
         title = "Figure 1. Counts of Theft Crime in All of Vancouver") +
    scale_fill_manual(labels = c('Not Theft', 'Theft'), values = c("#56B4E9",␣
↪"#009E73")) +
    theme(text = element_text(size = 12))
```



We quickly noticed Central Business District, the outlier, has way more crime than all other places in Vancouver. West Point Grey and Dunbar-Southlands have little crime in comparison, and their total crime count and proportion are pretty similar. Thus, it would be reasonable to use statistical inference on these two neighbourhoods for differences in theft proportion.

[8]:
```
crime_stats <- crime_overall %>%
    group_by(neighbourhood, type) %>%
    summarize(count = n(), .groups = 'drop') %>%
    pivot_wider(names_from = type,
                values_from = count) %>%
    mutate(total_crime = not_theft + theft,
           prop = theft / total_crime)

crime_stats = crime_stats[-1, ]

crime_stats %>%
    filter(total_crime > 1700 & total_crime < 2400)
```

A tibble: 6 × 5

neighbourhood <chr>	not_theft <int>	theft <int>	total_crime <int>	prop <dbl>
Arbutus Ridge	773	958	1731	0.5534373
Dunbar-Southlands	915	1250	2165	0.5773672
Kerrisdale	1031	1237	2268	0.5454145
Shaughnessy	936	957	1893	0.5055468
South Cambie	779	1319	2098	0.6286940
West Point Grey	801	1132	1933	0.5856182

We notice that West Point Grey and Dunbar-Southlands have a similar proportion of theft. Let us zoom in by filtering for the two neighbourhoods.

[9]:
```
crime_filtered <- crime_overall %>%
    filter(neighbourhood %in% c("West Point Grey","Dunbar-Southlands"))

head(crime_filtered)
```

A data.frame: 6 × 2

	type <chr>	neighbourhood <chr>
1	theft	West Point Grey
2	theft	West Point Grey
3	theft	West Point Grey
4	theft	West Point Grey
5	theft	West Point Grey
6	theft	West Point Grey

We then compute some initial observations about the filtered data and tidy it.

```
[10]: crime_type_pivot <- crime_filtered %>%
    group_by(neighbourhood, type) %>%
    summarize(count = n(), .groups = 'drop') %>%
    pivot_wider(names_from = type,
                values_from = count) %>%
    mutate(total_crime = not_theft + theft,
           prop = theft / total_crime)

crime_type_pivot
```

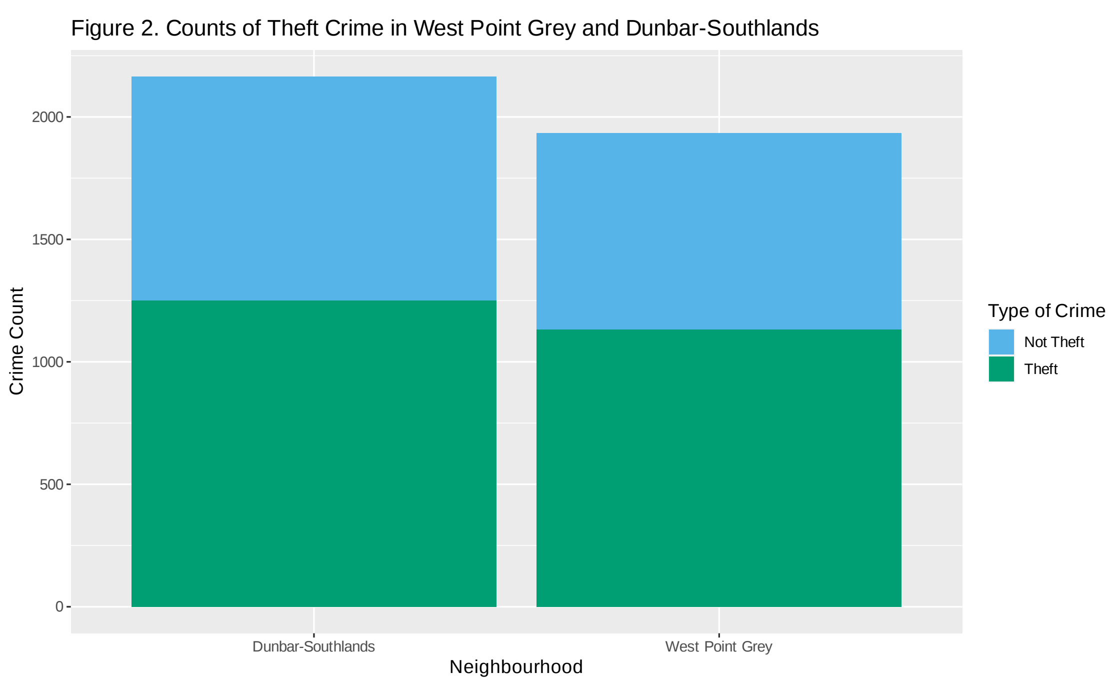
A tibble: 2 × 5

neighbourhood <chr>	not_theft <int>	theft <int>	total_crime <int>	prop <dbl>
Dunbar-Southlands	915	1250	2165	0.5773672
West Point Grey	801	1132	1933	0.5856182

Table 1. Initial observations of the crime data

We can zoom in on the two bars pertaining to West Point Grey and Dunbar-Southlands as follows.

```
[11]: ggplot(crime_filtered, aes(x = neighbourhood, fill = type)) +
    geom_bar() +
    labs(x = "Neighbourhood",
         y = "Crime Count",
         fill = "Type of Crime",
         title = "Figure 2. Counts of Theft Crime in West Point Grey and␣
 ↪Dunbar-Southlands") +
    scale_fill_manual(labels = c('Not Theft', 'Theft'), values = c("#56B4E9",␣
 ↪"#009E73")) +
    theme(text = element_text(size = 12))
```



From the plot and table, we observe that the proportion of theft crime are similar for the two neighbourhoods. West Point Grey is slightly higher in proportions, although Dunbar-Southlands has a greater count. Also, for both neighbourhoods, theft is the majority type of crime.

We now calculate the observed test statistic $\hat{p}_1 - \hat{p}_0$, which is the proportion of theft in West Point Grey subtracted by the proportion of theft in Dunbar-Southlands.

[12]:
```
crime_estimates <- crime_type_pivot %>%
    select(neighbourhood, total_crime, prop) %>%
    pivot_wider(names_from = neighbourhood, values_from = c(total_crime, prop))

colnames(crime_estimates) <- c('n_ds', 'n_wpg', 'p_ds', 'p_wpg')

crime_estimates <- crime_estimates %>%
    mutate(prop_diff = p_wpg - p_ds)

crime_estimates
```

A tibble: 1 × 5

n_ds <int>	n_wpg <int>	p_ds <dbl>	p_wpg <dbl>	prop_diff <dbl>
2165	1933	0.5773672	0.5856182	0.008251004

Table 2. Crime estimates

Based on the difference in proportions of 0.008251004 and the plot, we cannot easily conclude anything significant about the difference in proportions of theft in both neighbourhoods, meaning that we must use statistical inference.

3.0.2 Methods

We will be using both asymptotics and bootstrapping to conduct our research to discover whether West Point Grey has a higher proportion of theft compared to Dunbar-Southlands.

For asymptotics, we rely on the Central Limit Theorem because proportions do not follow a random distribution, meaning their distribution won't be normal. Therefore, we need to check for the large enough sample size condition, such that `n(1-p) >= 10` and `np >= 10`. We also need to assume that the sample is random and independent. By carrying out a two-sample independent z-test, we will use the test statistic:

$$Z = \frac{\hat{p}_1 - \hat{p}_2}{\sqrt{\hat{p}(1-\hat{p})\left(\frac{1}{n_1} + \frac{1}{n_2}\right)}}.$$

For bootstrapping, we will set a consistent seed to ensure data reproducibility. Afterwards, we take bootstrap samples from our crime dataset to create a bootstrap distribution for the difference in proportions.

For both approaches, we find the p-value to check for any statistically significant findings to decide whether we can reject the null hypothesis or not under a significance level of $\alpha = 0.05$. This also means a confidence level of 95% which we can construct using both methods to capture with a certain degree of confidence that the true difference in proportions falls within the interval.

3.0.3 Results Using Asymptotics

We conduct a two-sample z-test to calculate the proportion difference. Recall that we already have the counts and proportions of crime in both neighbourhoods in `crime_estimates`.

[13]:
```
crime_estimates
```

A tibble: 1×5

n_ds	n_wpg	p_ds	p_wpg	prop_diff
<int>	<int>	<dbl>	<dbl>	<dbl>
2165	1933	0.5773672	0.5856182	0.008251004

Table 2. Crime estimates

Since we are using theory-based methods, we check that `np >= 10` and `n(1-p) >= 10` for both neighbourhoods. We have $2165 * 0.5773672 \approx 1250 \geq 10$ and $2165 * (1 - 0.0.5773672) \approx 915 \geq 10$ for Dunbar-Southlands. Likewise for West Point Grey, $1933 * 0.5856182 \approx 1130 \geq 10$ and $1933 * 0.5856182 \approx 800 \geq 10$. Aside from satisfying the 'success-failure' condition for a large enough sample size, We assume that the sample dataset is random and the data are independent of each other, so we can use the Central Limit Theorem.

We proceed to calculate the null distribution standard error by first calculating a pooled proportion.

[14]:
```
crime_asymptotics <- crime_estimates %>%
    mutate(pooled_proportion = (n_ds*p_ds + n_wpg*p_wpg) / (n_ds + n_wpg),
           null_std_error = sqrt(pooled_proportion * (1-pooled_proportion) * (1/n_ds + 1/n_wpg)))

crime_asymptotics
```

A tibble: 1×7

n_ds	n_wpg	p_ds	p_wpg	prop_diff	pooled_proportion	null_std_error
<int>	<int>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>
2165	1933	0.5773672	0.5856182	0.008251004	0.5812592	0.01543827

Table 3. Parameters calculated from asymptotics

We can now easily find a 95% confidence interval using asymptotics.

[15]:
```
obs_prop_diff_asymptotics <- crime_asymptotics$prop_diff
null_std_error <- crime_asymptotics$null_std_error

prop_ci_asymptotics <- tibble(
    lower_ci = qnorm(0.025, obs_prop_diff_asymptotics, null_std_error),
    upper_ci = qnorm(0.975, obs_prop_diff_asymptotics, null_std_error))

prop_ci_asymptotics
```

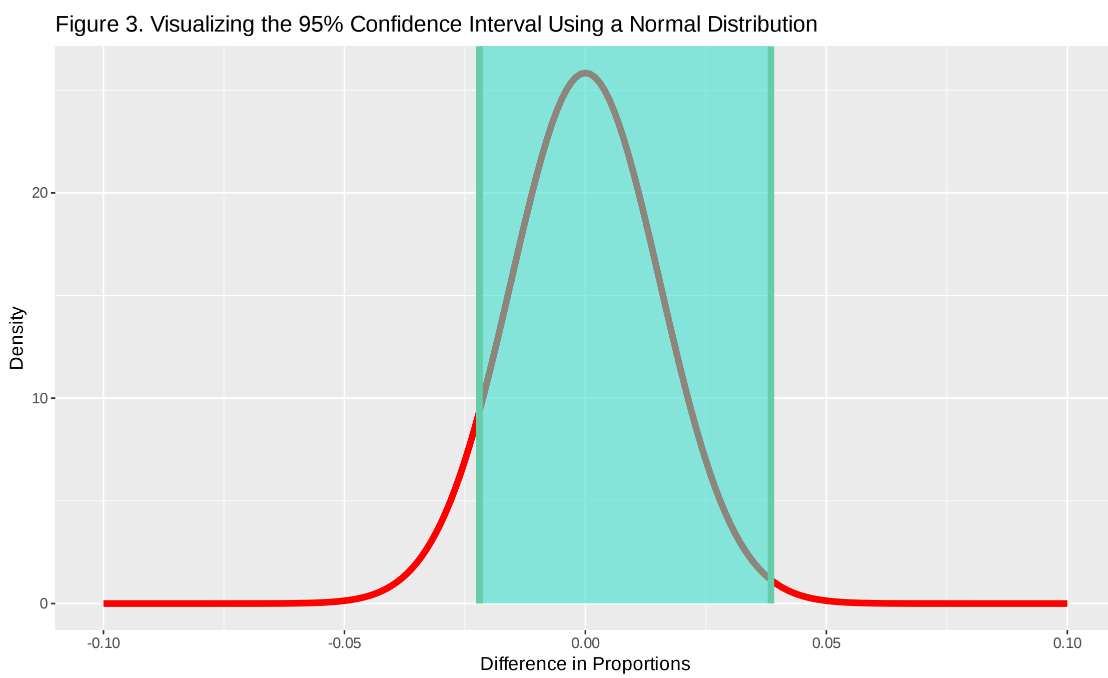
A tibble: 1×2

lower_ci	upper_ci
<dbl>	<dbl>
-0.02200745	0.03850946

Table 4. Asymptotics Confidence Interval

We note that 0 is included in the interval, meaning that is is likely that we fail to reject the null hypothesis. We can also visualize this confidence interval.

[16]:
```
x = seq(-0.1, 0.1, by = 0.001)
y <- dnorm(x, 0, null_std_error)
normal_data <- tibble(x, y)

normal_data %>%
    ggplot(aes(x, y)) +
    geom_line(color = 'red', lwd = 2) +
    shade_confidence_interval(endpoints = prop_ci_asymptotics) +
    labs(x = "Difference in Proportions",
         y = "Density",
         title = "Figure 3. Visualizing the 95% Confidence Interval Using a␣
 ↪Normal Distribution")+
    theme(text = element_text(size = 12))
```



We are 95% confident that the true difference in proportions is captured by the confidence interval created using asymptotics.

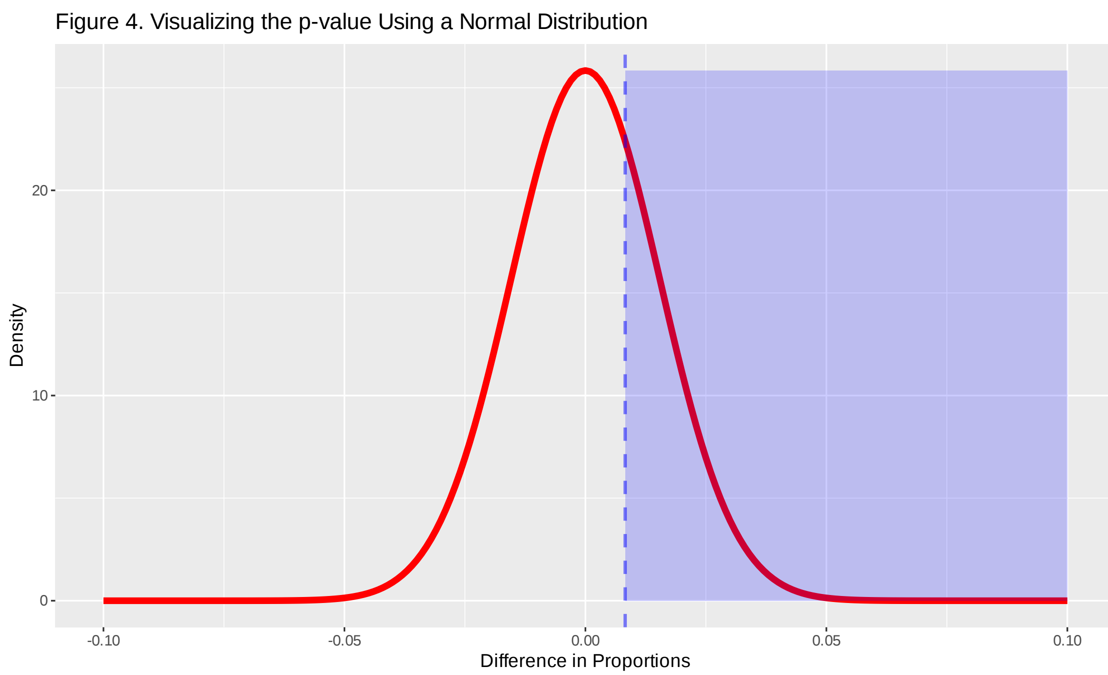
Finally, we obtain the p-value.

[17]:
```
p_value_asymptotics <- pnorm(obs_prop_diff_asymptotics, 0, null_std_error,␣
 ↪lower.tail=F)
p_value_asymptotics
```

0.296514658808924

Clearly, the p-value above is greater than the significance level we set at 0.05, indicating that we fail to reject the null hypothesis. We can visualize this result with a plot.

[18]:
```
normal_data %>%
    ggplot(aes(x, y)) +
    geom_line(color = 'red', lwd = 2) +
    geom_ribbon(aes(xmin = obs_prop_diff_asymptotics,
                    xmax = max(x)),
                    alpha = 0.2,
                    fill = 'blue') +
    geom_vline(xintercept = obs_prop_diff_asymptotics,
               lwd = 1, alpha = 0.5, color = 'blue', linetype = 'dashed') +
    labs(x = "Difference in Proportions",
         y = "Density",
         title = "Figure 4. Visualizing the p-value Using a Normal␣
 ↪Distribution") +
    theme(text = element_text(size = 12))
```



We use `prop.test` to check our answer.

[19]:
```
c_wpg <- crime_estimates$n_wpg * crime_estimates$p_wpg
c_ds <- crime_estimates$n_ds * crime_estimates$p_ds

prop_test <- tidy(
```

```
    prop.test(x = c(c_wpg, c_ds),
              n = c(crime_estimates$n_wpg, crime_estimates$n_ds),
              correct = FALSE,
              alternative = "greater"))
prop_test
```

A tibble: 1 × 9

estimate1	estimate2	statistic	p.value	parameter	conf.low	conf.high	method
<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<dbl>	<chr>
0.5856182	0.5773672	0.2856382	0.2965147	1	-0.01713783	1	2-sample

The p-value using asymptotics and prop.test gives us the same result, but we expect it to be slightly different from using the infer package.

3.0.4 Results Using the Infer Package for Bootstrapping

We first obtain the null model after setting the seed to make the analysis reproducible. The response variable is `type` and the explanatory variable is `neighbourhood`. Assuming the samples are independent, we generate replicates of shuffled data with the `permute` argument. Recall that we are calculating a difference in proportions of West Point Grey subtracted by Dunbar-Southlands.

[20]:
```
set.seed(1)

null_model <- crime_filtered %>%
    specify(type ~ neighbourhood, success = "theft") %>%
    hypothesise(null = "independence") %>%
    generate(reps = 2000, type = "permute") %>%
    calculate(stat = "diff in props", order = c("West Point Grey",␣
 ↪"Dunbar-Southlands"))
head(null_model)
```

A infer: 6 × 2

replicate	stat
<int>	<dbl>
1	-0.01622960
2	-0.02308417
3	0.02000170
4	-0.01329193
5	-0.02014650
6	-0.02798030

Now, we calculate the observed proportion difference, which should give the same answer as in `crime_estimates`

[21]:
```
crime_estimates
```

A tibble: 1 × 5

n_ds	n_wpg	p_ds	p_wpg	prop_diff
<int>	<int>	<dbl>	<dbl>	<dbl>
2165	1933	0.5773672	0.5856182	0.008251004

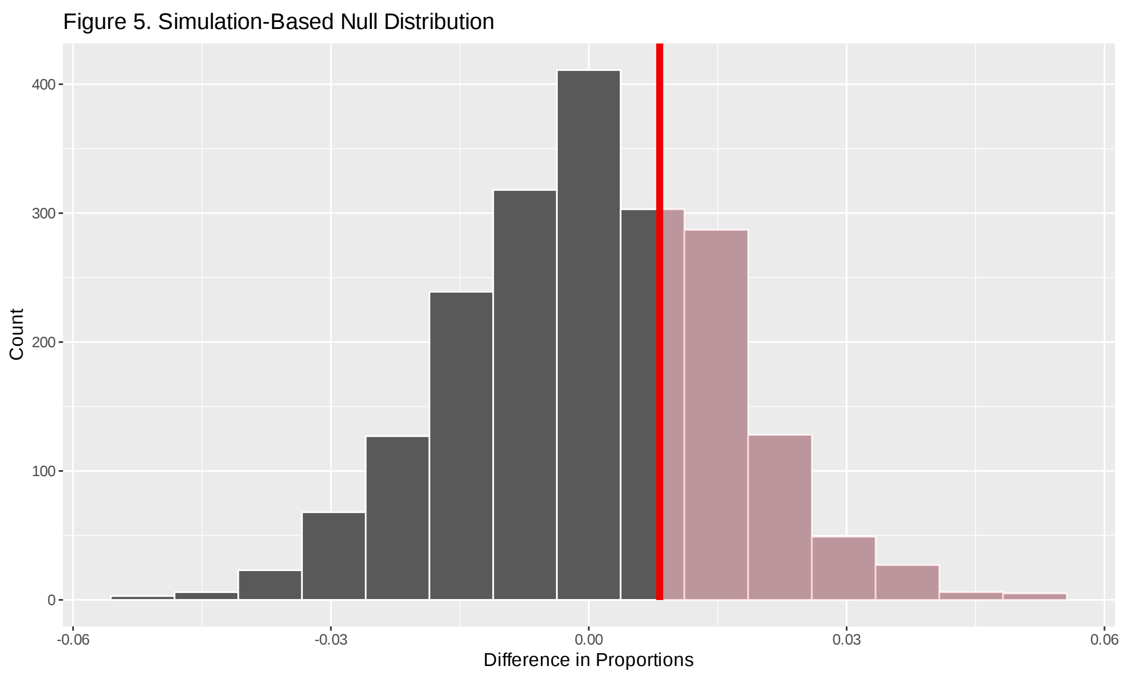
Table 2. Crime estimates

[22]:
```
obs_prop_diff <- crime_filtered %>%
    specify(type ~ neighbourhood, success = "theft") %>%
    calculate(stat = "diff in props", order = c("West Point Grey",␣
 ↪"Dunbar-Southlands")) %>%
    pull()
obs_prop_diff
```

0.00825100449348803

As expected, the observed difference in proportions match, so we move onto visualizing the simulation-based null distribution.

[23]:
```
theft_result_plot <-
   null_model %>%
   visualize() +
   shade_p_value(obs_stat = obs_prop_diff, direction = "right") +
   labs(x = "Difference in Proportions",
        y = "Count",
       title = "Figure 5. Simulation-Based Null Distribution") +
    theme(text = element_text(size = 12))
theft_result_plot
```



We can compute the p-value using `get_p_value`.

[24]:
```
p_value_infer <- null_model %>%
    get_p_value(obs_stat = obs_prop_diff, direction = "right") %>%
```

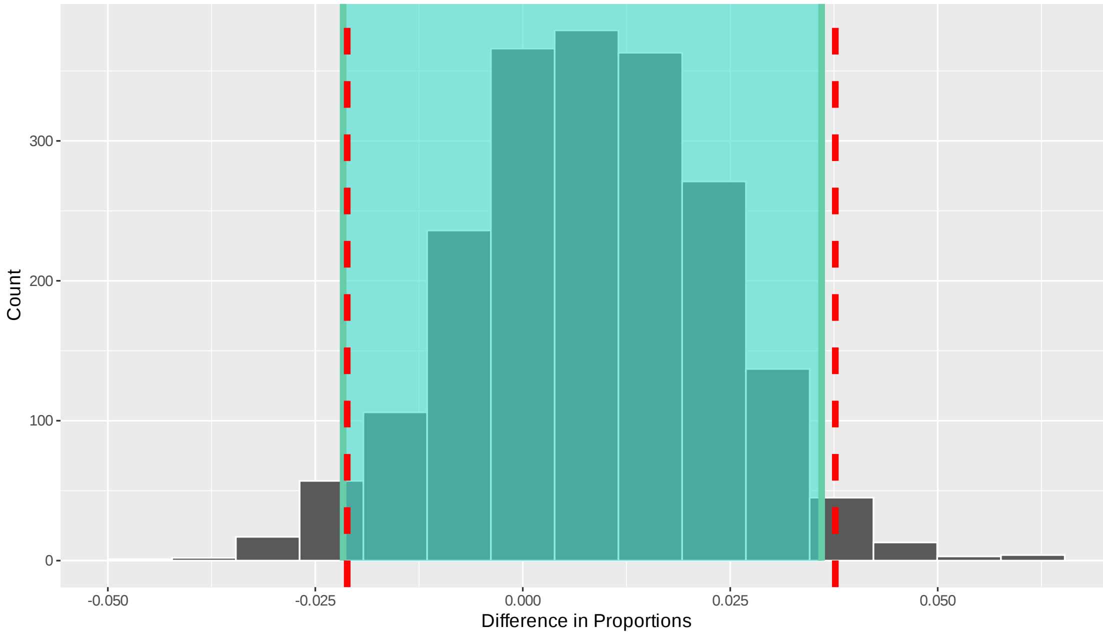
```
    pull()
p_value_infer
```

0.3185

Now, we will jump from conducting the hypothesis test to calculating a 95% confidence interval using the percentile and standard error method by bootstrapping from our crime sample.

[25]:
```
bootstrap_distribution <- crime_filtered %>%
    specify(type ~ neighbourhood, success = "theft") %>%
    generate(reps = 2000, type = "bootstrap") %>%
    calculate(stat = "diff in props", order = c("West Point Grey",␣
 ↪"Dunbar-Southlands"))

percentile_ci <- bootstrap_distribution %>%
    get_confidence_interval(level = 0.95, type = 'percentile')

se_ci <- bootstrap_distribution %>%
  get_confidence_interval(level = 0.95, type = "se",
                          point_estimate = obs_prop_diff)

visualize(bootstrap_distribution) +
    shade_confidence_interval(endpoints = percentile_ci) +
    labs(x = "Difference in Proportions",
         y = "Count",
         title = "Figure 6. Simulation-Based Bootstrap Distribution with 95%␣
 ↪Confidence Interval Shaded") +
    theme(text = element_text(size = 12)) +
    geom_vline(xintercept = pull(se_ci[1]), linetype = 'dashed', lwd = 2,␣
 ↪colour = 'red') +
    geom_vline(xintercept = pull(se_ci[2]), linetype = 'dashed', lwd = 2,␣
 ↪colour = 'red')
```

Figure 6. Simulation-Based Bootstrap Distribution with 95% Confidence Interval Shaded



The shaded portion represents the 95% confidence interval using the percentile method, while the other uses the standard error theory-based method.

Now that we have calculated the results for our research, let us summarize them in two tables. The first one shows the confidence intervals using both methods, while the latter shows the p-values.

[26]:
```
types <- tibble(type = c("asymptotics", "bootstrap_percentile", "bootstrap_se"))
combined_ci <- rbind(prop_ci_asymptotics,
                     percentile_ci,
                     se_ci)

cbind(types, combined_ci)
```

A data.frame: 3 × 3

type	lower_ci	upper_ci
<chr>	<dbl>	<dbl>
asymptotics	-0.02200745	0.03850946
bootstrap_percentile	-0.02164928	0.03601064
bootstrap_se	-0.02115698	0.03765899

Table 5. Confidence interval comparison

[27]:
```
p_types <- tibble(type = c("asymptotics", "bootstrap"))
combined_p <- tibble(p_value = c(p_value_asymptotics, p_value_infer))

cbind(p_types, combined_p)
```

A data.frame: 2 × 2

type	p_value
<chr>	<dbl>
asymptotics	0.2965147
bootstrap	0.3185000

Table 6. P-value comparison

Doing a quick comparison, we see that each of the 95% confidence intervals capture 0, and that all the intervals produced by the different methods have little deviation. We can then say across all 95% confidence intervals that could be calculated, we can expect that 95% of the intervals contain the true difference in theft crime proportions. Similarly, the p-value of using asymptotics and bootstrapping are both at approximately 0.3, which is significantly greater than the 5% significance level, so we fail to reject the null hypothesis. In other words, we do not have enough evidence to demonstrate that West Point Grey has a higher theft rate than Dunbar-Southlands, resulting in the possibility of committing a Type II Error.

Comparing the two methods, asymptotics analyze the sample dataset directly based on theoretical methods while bootstrapping is known to mimic the shape and spread of the sampling distribution itself, thus giving similar results since they both have the underlying goal of understanding the sampling distribution of the population. As seen above, the confidence intervals and p-value only differ slightly due to sampling variation. Since we ensured that the assumptions to use the Central Limit Theorem were met, it is expected that the bootstrapping and asymptotic methods should produce similar results.

Although bootstrapping is very versatile and can be applied without any assumptions and conditions, asymptotics is preferred in our case. With a large sample size of over 1000 observations, theory-based method is not only accurate but also computationally inexpensive with only a few mathematical calculations, while the bootstrap approach relies more heavily on the given sample.

4 3. Discussion

4.0.1 Summary

In our study of determining whether or not there is a statistically significant difference in the proportion of theft crime occurring in West Point Grey against Dunbar-Southlands, we fail to reject the null hypothesis stating there is no difference between the neighbourhoods at a significance level of 5%. Originally, we expected West Point Grey to have a higher proportion of theft compared to Dunbar-Southlands as the population density would be higher closer to campus, leading to a higher theft rate. However, both the asymptotic analysis based on the Central Limit Theorem and bootstrap analysis fail to reject the null hypothesis. We obtained confidence intervals containing the value of 0, or no difference, and achieved p-values of approximately 0.3. This means that using both the theory-based approach and simulation-based approach gave us the same conclusion, so we can be relatively confident in our answer.

4.0.2 Significance

Our findings could impact residents living in either neighbourhoods, if not both, to be more proactive and aware of theft in their area and enforce relevant safety measures. Since we specifically targeted the neighbourhoods of West Point Grey and Dunbar-Southlands, two of the most popular neighbourhoods for off-campus housing pertaining to University of British Columbia students, then these students can become more informed on the theft proportions in these places. However, since we discovered no statistical significance between the two neighbourhoods in terms of theft proportion, then individuals should not be too wary of living in either neighbourhood.

4.0.3 Further Questions

One drawback of our study is that while big data may explain differences in the danger of theft and support governmental measures, it cannot explain individual cases or provide a detailed plan of how to minimize risks. Furthermore, a challenge we face is how to extrapolate our analysis to predict future crime rates, as that is crucial for reducing crime rates. Despite not finding any statistical difference between the proportion of theft in West Point Grey and Dunbar-Southlands, we have further questions regarding the underlying motivations behind theft and what features cause a difference in theft between different neighbourhoods. Not only that, our research raises further questions into crimes not limited to just theft, but extended further to other crime types such as homicides or residential break-ins.

Word count: 1870

5 4. References

Branch, Legislative Services. "Consolidated Federal Laws of Canada, Criminal Code." Criminal Code, 27 July 2023, laws-lois.justice.gc.ca/eng/acts/c-46/section-322.html.

Crime Statistics. "Crime Statistics." Vancouver Police Department, 19 July 2023, vpd.ca/crime-statistics/.

Government of Canada, Department of Justice. "State of the Criminal Justice System - 2019 Report." Results by Outcome, 7 July 2021, www.justice.gc.ca/eng/cj-jp/state-etat/2019rpt-rap2019/p7.html.

UBC. "Your Guide to Neighborhoods in Vancouver: UBC Vantage College." Your Guide to Neighborhoods in Vancouver | UBC Vantage College, vantagecollege.ubc.ca/blog/your-guide-neighborhoods-vancouver. Accessed 30 July 2023.

Vancouver Police Department. "Vancouver Police Department Crime Data." Accessed 30 July 2023.