W203: Statistics for Data Science

Lab 2: Comparing Means

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Abstract

Hypothesis testing of parametric and non-parametric data sets represent key tasks evaluated within this lab. Frequentist statistics techniques are used to answer a series of questions derived from the ANES 2018 Pilot Study. Key aspects evaluated include the identification of relevant assumptions, development of null & alternative hypotheses and the assessment of statistical & practical significance.

Overview

The mission of the American National Election Studies (ANES) is to advance the scientific study of public opinion and political behavior. They accomplish this by developing and employing surveys that measure many variables and support rich hypothesis testing to assess voter turnout and vote choice. The origins of their analysis started with a nation opinion survey conducted at the University of Michigan's Survey Research Center with the 1948 presidential election. They continued to conduct surveys in every presidential election year through 2004. In 2006, Stanford University's Institute for Research in the Social Sciences and the University of Michigan's Institute for Social Research developed a partnership which maintains and evolves the ANES.

Through the decades, Time Series studies conducted before and after presidential elections represent the focus of ANES studies. Typically collection occurs via face-to-face interviews with respondents in their homes. Pilot Studies are used to test and refine new questions for the Time Series. These supporting studies are conducted telephonically. The data assessed in this lab is from the 2018 Pilot Study.

ANES studies use procedures known as complex sampling instead of simple random sampling. Some of the key methods that make ANES samples complex include:

- Oversampling.
- Startified cluster sampling.
- Within household sampling.

```
setwd("~/Desktop/w203_lab2/w203_lab2")
anes_data <- read.csv("~/Desktop/W203/homework/lab_2/anes_pilot_2018.csv")
library(knitr)
opts_chunk$set(tidy.opts=list(width.cutoff=45),tidy=TRUE)
```

1. Do US voters have more respect for the police or for journalists?

Overview.
Within the ANES pilot questions, two specific ones directly support the posed question:

- How would you rate the police?
- How would you rate journalists?

Though these questions do not provide a holistic assessment of public opinion, the do provide a start point for an initial perspective on opinion trends.

Figure 1: 2018 ANES Feeling Thermometer

Operationalization.
The context of these questions was in a 'feeling thermometer', as depicted in Figure 1. Using this approach, each respondent provides a numberical value which is in a categorical range from 0 too 100. An issue with these questions is that they are structured to assess 'feelings towards' instead of 'respect for'. A further feature of this thermometer is the varied interpretation of the scale by respondents.

Values existed for all respondents for these two questions. The expected range of the data for each of these survey questions is [0,100]. The police data meets this criteria; however, the press data does not. This question possesses negative values, which indicates these was no respondent answer. To prevent the results from being skewed by these values, the responses associated with those respondents were not included in the analysis. Using this approach, the overall number of respondents reduced by 2. The final data set analysed possessed data from 2498 respondents with values from 0 to 100 for both the press and police questions.

Exploratory Data Analysis.

```
press <- anes_data$ftjournal
police <- anes_data$ftpolice
press_range <- range(press)  # press_range # [-7,100]
police_range <- range(police)  # police_range # [0,100]
trust_data <- data.frame(police, press)
# subset(press_data, press == -7) press_data
# <- press_data[!subset(press_data, press ==
# -7)]
```

```r
trust_data <- trust_data[-c(51), ]  # delete row with -7 value
trust_data <- trust_data[-c(597), ]  # delete row with -7 value
```

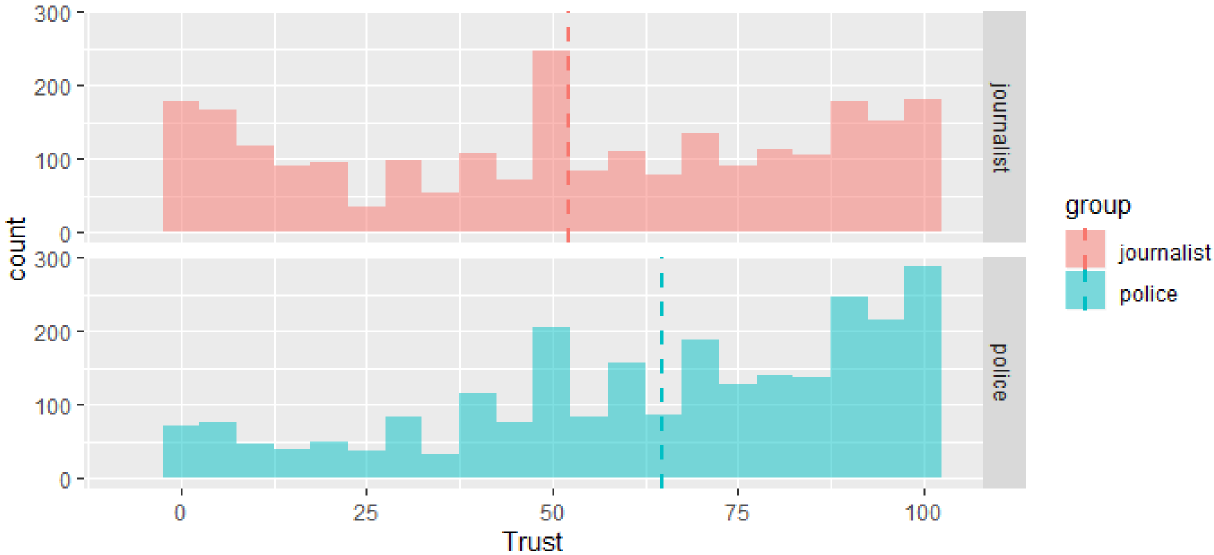


Figure 2: Journalist Police Trust

Analysis
Though the data is numberical in nature, indivduals will use different scales when assessing their relative values on the thermometer. Consequently, a linear relationship cannot be assumed to exist between the values. This data feature supports the use of a non-parametric hypothesis test - namely the Wilcoxon Rank-Sum Test. Employing the Hypothesis of Means for H_O for this analysis capitalizes on the metric scale that the thermometer context provides. For this question, the hypotheses tested were:

- Null: The means of the two groups is the same. $H_0 : E(Press) = E(Police)$

- Alternative: The means of the two groups are not the same. $H_A : E(Press) \neq E(Police)$

```r
x <- trust_data$police  # police data
y <- trust_data$press  # press data
# length(x); length(y)
wilcox.test(x, y, paired = FALSE, mu = 0, conf.level = 0.95)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  x and y
## W = 3800504, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
```

Outcome.
Statistical Signficance. The p-value obtained from the Wilcoxon rank-sum test supports rejecting the null hypotheses - namely that there is no translation in the distributions of public opinion of the police and the press.
Practical Significance. Spearman's rank correlation coefficient represents an effective way to assess the practical significance of the police and press analysis. It provides a non-parametric measure of rank correlation, which aligns to the hypothesis test.

```r
cor(x, y, method = "spearman")
```

```
## [1] -0.1233844
```

- The values for Spearman's Rank-Order Correlation, r_s, can take on the values from $+1$ to -1. r_s has the following associations:
  - $+1$: perfect association of ranks
  - 0: no association between the ranks
  - -1: perfet negative association of ranks.

The r_s value obtained from this test was -0.123. This indicates a weak negative correlation between the public opinion of the press and the police.

2. Are Republican voters older or younger than Democratic voters?

Overview.
Of keen interest in politics is the age of voters. This has emerged as a topic of interest with the pubilc as it relates to enhanced gun control laws. Youth affected by school mass shootings have opened the debate on whether the federal voting age in the United States should be lowered from 18 to 16. The 26th Ammendment to the US Constitution establishes the voting age. Though it was originally set at 21 years of age, a student movement in the 1960s in the midst of the Vietnam War lobbied for the age to be dropped to 18. Armed with the slogan: old enough to fight, old enough to vote', the movement successfully lobbied Congress to lower the voting age to 18 for national elections.

Operationalization.
Two entries within the survey directly support establishing a frame for this question. These two questions are:
- What year were you born?
- Generally speaking, do you usually think of yourself as a Democrat, a Republican, an Independent, or what?

Together, these questions, along with the assmption that surveyed individuals provided truthful data for these questions, creates an informed estimate for approaching the question of which party has older voters. The age of the respondent is a numberical value which subtracts 2018 from the provided respondent birth year. Their party affiliation is categorical, and is a best estimate assessment of an individual's political association.

Exploratory Data Analysis.
This type of data supports using the independent sample t-test. One set of data is numberical (respondents' ages), and the other is categorical (Republican or Democrat). With this test, we conducted a comparison of means. The hypotheses being tested were:

$$H_0 : E(Republicans) = E(Democrats)$$
$$H_A : E(Republicans) \neq E(Democrats)$$

Assumptions needed for this analysis include:
- Metric scale. The age data meets this assumption.
- Each value pair is drawn independent of other pairs from the same distribution. - The two variables have the same distribution, just with some potential shift.

```
partisans = anes_data[which(anes_data$pid1d ==
    c(1, 2)), ]  # 1 = democrat, 2 = republican
age = 2018 - partisans$birthyr
party = partisans$pid1d
partisanAge = data.frame(age, party)
```

Analysis.

```
t.test(age ~ party, data = partisans)
```

```
##
##  Welch Two Sample t-test
##
## data:  age by party
## t = -0.60281, df = 347.32, p-value = 0.547
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -4.450148  2.362228
## sample estimates:
## mean in group 1 mean in group 2
##        51.74771        52.79167
```

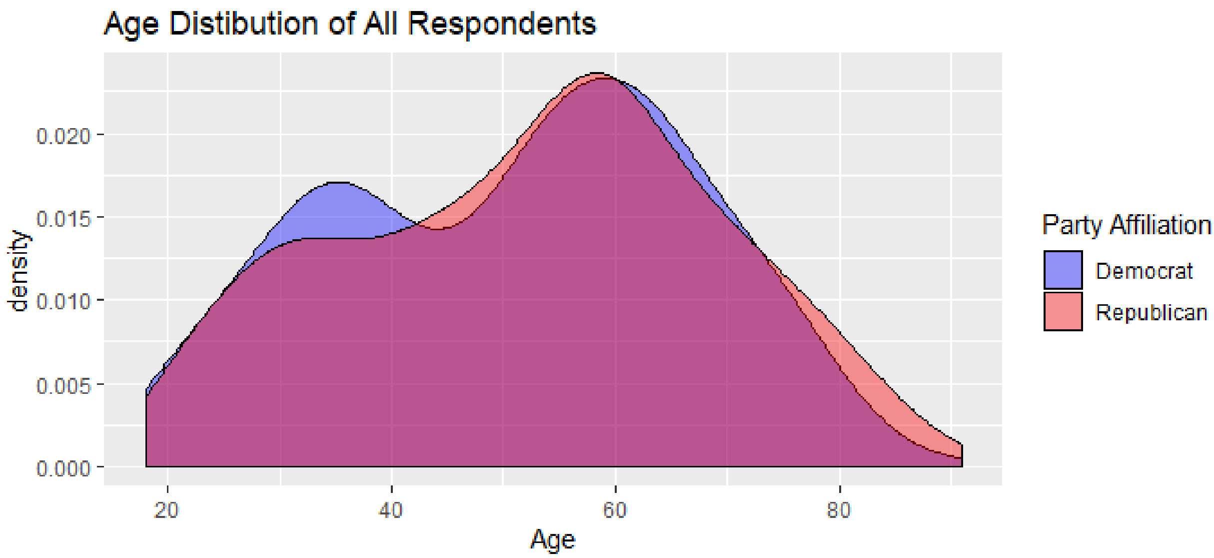


Figure 3: All Respondents

Statistical signifcance. The high p-value from this test, 0.547 indicates that the null hypothesis cannot be rejected.

Practical significance. The Cohen's d test supports determining the effect size for the analysis. With this test, the outcome value (d = -0.0624) indicates that there is only a small effect present with this test.

```
library(effsize)
cohen.d(age ~ party, data = partisans)
```

```
## Warning in cohen.d.formula(age ~ party, data = partisans): Cohercing rhs of
## formula to factor
```

```
##
## Cohen's d
##
## d estimate: -0.06240283 (negligible)
## 95 percent confidence interval:
##      lower      upper
## -0.2643016  0.1394960
```

Thus far, we have only addressed individuals who identified themselves as either Republicans or Democrats. What has yet to be addressed is whether they voted. One of the survey questions captures whether respondents voted in the election held the month prior (November 2018). Integrating this criteria into the dataset gives some further insights into party voters.

```
partisansVoted = partisans[which(partisans$turnout18 ==
    c(1, 2, 3)), ]
```

```
## Warning in partisans$turnout18 == c(1, 2, 3): longer object length is not a
## multiple of shorter object length
```

```
t.test(2018 - partisansVoted$birthyr ~ partisansVoted$pid1d,
    data = partisansVoted)
```

```
##
##  Welch Two Sample t-test
```

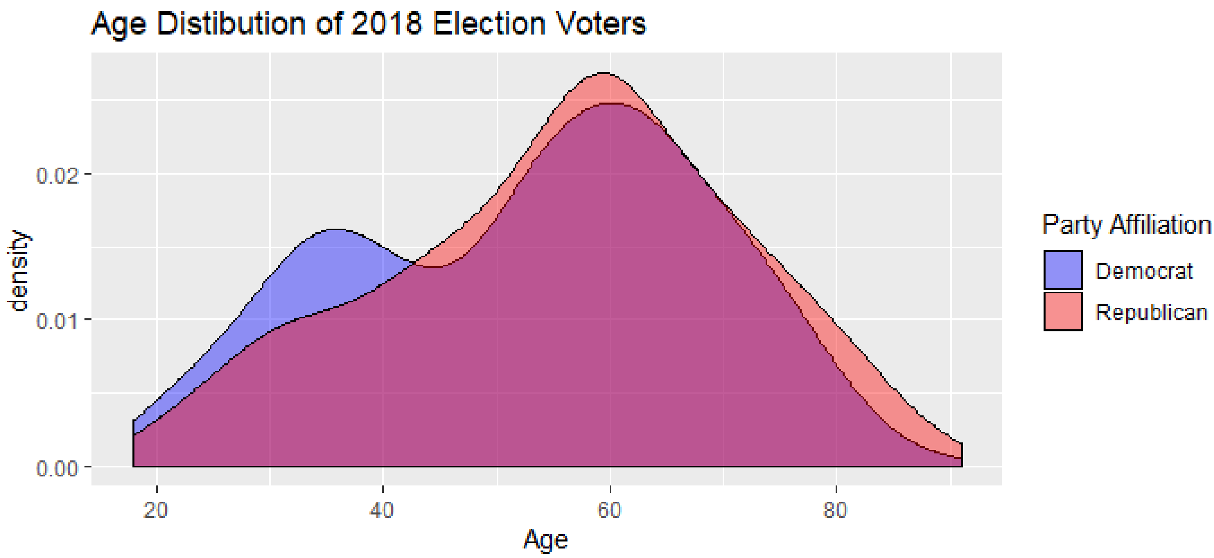


Figure 4: Voted Age Distribution

```
##
## data:  2018 - partisansVoted$birthyr by partisansVoted$pid1d
## t = -3.3955, df = 104.02, p-value = 0.0009709
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -15.257998  -4.006959
## sample estimates:
## mean in group 1 mean in group 2
##        51.12308        60.75556
```

Outcome.
Including the constraint of having voted in the previous month's election conveys a distinctly different picture. The p-value no longer supports not rejecting the null hypothesis. The data does not support that the difference in means is zero. A point of note is that for the Democrats, the average age between the two scenarios stayed quite constant (51.7 and 51.1). However, for the Republicans, the average age of those that voted in the November election was 8 years older than Republicans at large from the survey.

```
library(effsize)
cohen.d(2018 - partisansVoted$birthyr ~ partisansVoted$pid1d,
    data = partisansVoted)
```

```
## Warning in cohen.d.formula(2018 - partisansVoted$birthyr ~
## partisansVoted$pid1d, : Cohercing rhs of formula to factor
```

```
##
## Cohen's d
##
## d estimate: -0.6376504 (medium)
## 95 percent confidence interval:
##      lower      upper
## -1.0313752 -0.2439256
```

Re-assessing the practical significance of the results on the adjusted dataset with the Cohen's d test now indicates a medium effect size. These results indicate that the average age of Democrats at large in the survey and those that voted in the November 2018 election are consistent. However, Republicans that voted in the

November 2018 election are on average 8 years older than Republicans at large in the survey.

3. Do a majority of independent voters believe that the federal investigations of Russia election interference are baseless?

Overview.
Prior to the 2016 presidential election, members of the US Congress publically disclosed the existence of attempted Russian interference activities. Robert Mueller, a former FBI director, led a Special Counsel Investigation from May 2017 to March 2019. This survey occurred while this Mueller's investigation was ongoing.

Operationalization.
Within the survey a specific section was dedicated to the Russia/Trump campaign investigation. One question specifically addressed the Mueller Investigation, while the other two explicitly addressed public opinion regarding the Russian interference in the campaign.

- Do you think the Russian government probably interfered in the 2016 presidential election to try and help Donald Trump win, or do you think this probably did not happen?

- Do you think Donald Trump's 2016 campaign probably coordinated with the Russians, or do you think his campaign probably did not do this?

Both questions have potential to provide some insight into the question at hand, assuming that respondents provided honest answers. The survey question is close to the question at hand. Assessing the available data will help frame which ones best inform the analysis.

Exploratory Data Analysis.

```
russia_involvement <- data.frame(anes_data$pid1d,
    anes_data$turnout18, anes_data$russia16, anes_data$coord16)
colnames(russia_involvement) <- c("party", "voted",
    "russia_1", "russia_2")
russia_involvement <- russia_involvement[which(russia_involvement$party ==
    c(3)), ]  # isolate independent voters
russia_involvement <- russia_involvement[which(russia_involvement$voted ==
    c(1, 2, 3)), ]  # isolated those who voted in 2018
```

```
## Warning in russia_involvement$voted == c(1, 2, 3): longer object length is not a
## multiple of shorter object length
```

```
summary(russia_involvement$russia_1)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.423   2.000   2.000
```

```
summary(russia_involvement$russia_2)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.487   2.000   2.000
```

Analysis.
Both sets of data capture two different values, [1,2] with 1 indicating influence/coordination and 2 indicating the opinion that there was not Russian involvement. 78 data points exist, so the criteria of the central limit theorem is supported. With only one numberial value in question, a parametric test is appropriate. The student's t-test provides a viable tool for conducting hypothesis testing. The test structure is as follows: - H_0: Russian influence exists, $\mu_0 = 1$ - H_A: $\mu \neq 1$ This will be conducted as a two-tail test.

```r
t.test(russia_involvement$russia_1, alternative = c("two.sided"),
    mu = 1)
```

```
##
##  One Sample t-test
##
## data:  russia_involvement$russia_1
## t = 7.5144, df = 77, p-value = 8.708e-11
## alternative hypothesis: true mean is not equal to 1
## 95 percent confidence interval:
##  1.310965 1.535188
## sample estimates:
## mean of x
##  1.423077
```

```r
t.test(russia_involvement$russia_2, alternative = c("two.sided"),
    mu = 1)
```

```
##
##  One Sample t-test
##
## data:  russia_involvement$russia_2
## t = 8.5528, df = 77, p-value = 8.74e-13
## alternative hypothesis: true mean is not equal to 1
## 95 percent confidence interval:
##  1.373755 1.600604
## sample estimates:
## mean of x
##  1.487179
```

```r
cohen.d(russia_1 ~ russia_2, data = russia_involvement)
```

```
## Warning in cohen.d.formula(russia_1 ~ russia_2, data = russia_involvement):
## Cohercing rhs of formula to factor
```

```
##
## Cohen's d
##
## d estimate: -3.63318 (large)
## 95 percent confidence interval:
##     lower     upper
## -4.367487 -2.898874
```

Outcome.

Statistical Significance. The p-values for these tests, p = 8.74e-13 and 8.708e-11 both support rejecting the null hypothesis. **Practical Significance.** The Cohen's d effect size value, d = -3.633, indicates that there is a large effect present between the two survey questions.

A particularly interesting feature amongst respondants is that their responses almost completely align to party lines. When re-doing the data for respondents that voted for each of the identified parties - Republican, Democrat, and Independent, each outcome is unique.

```r
library(knitr)
Independent_Russia <- c(1.423, 1.487)
Democrats_Russia <- c(1.025, 1.058)
Republicans_Russia <- c(1.848, 1.962)
```

```r
headers <- c("Independent", "Democrat", "Republican")
russia_outcome <- data.frame(Independent_Russia,
    Democrats_Russia, Republicans_Russia)
kable(russia_outcome, caption = "Russia Coordination Perception",
    col.names = headers)
```

Table 1: Russia Coordination Perception

Independent	Democrat	Republican
1.423	1.025	1.848
1.487	1.058	1.962

Survey respondents consistently aligned to their party affiliation - Democrats aligned to the presence of influence, while Republicans were skewed towards the opinion of no involvment. Independent affiliated respondents roughly split the diffence between the two extremes.

4. Was anger or fear more effective at driving increases in voter turnout from 2016 to 2018?

Overview.
Voter turnout varies greatly by state. Many factors influence this to include:

- **Electoral Competitiveness.** Voters in the 12 most competitive states tend to turn out at a higher rate than those in the other 39 states and the District of Columbia.
- **Election Type.** Primary elections and off-year state elections consistently have low turn-outs.
- **Voting Laws.** Early voting and accessability of polling places impact voter turnout.
- **Demographics.** Age, wealth, education, and gender all have identifable impacts on voter turnout. Amidst all these factors, this question singles out one specifically. It seeks to understand the impact that anger and fear had on voter turnout.

Operationalization.
No set of questions directly answers this question. this question was approached in two parts: identify voters in 2016 and 2018, and then identify what makes them fearful or angry. To identify voters, the questions addressing voter turnout in 2016 and 2018 provide the best initial insight on voting respondents.

First we should check our data for consistency:

```r
summary(anes_data$turnout16)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   1.000   1.306   2.000   3.000
```

```r
summary(anes_data$turnout18)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##   1.000   1.000   2.000   2.392   4.000   5.000
```

There are no non-responses, only respondents who are not sure if they voted, as per the codebook. We can filter these to find respondents who are sure they voted in 2016 and in 2018. We can see an increase of 1 vote from 2018 to 2016, so it appears that the principle assumption of this question, that there was an increase in votes 2018 vs 2016, is incorrect.

```r
# get all of our voters from 2016 who are sure
# they voted
voters16 = anes_data[which(anes_data$turnout16 ==
    1), ]

# get all of our voters from 2018 who are sure
# they voted
voters18 = anes_data[which(anes_data$turnout18 <
    4), ]
nrow(voters18) - nrow(voters16)
```

```
## [1] 1
```

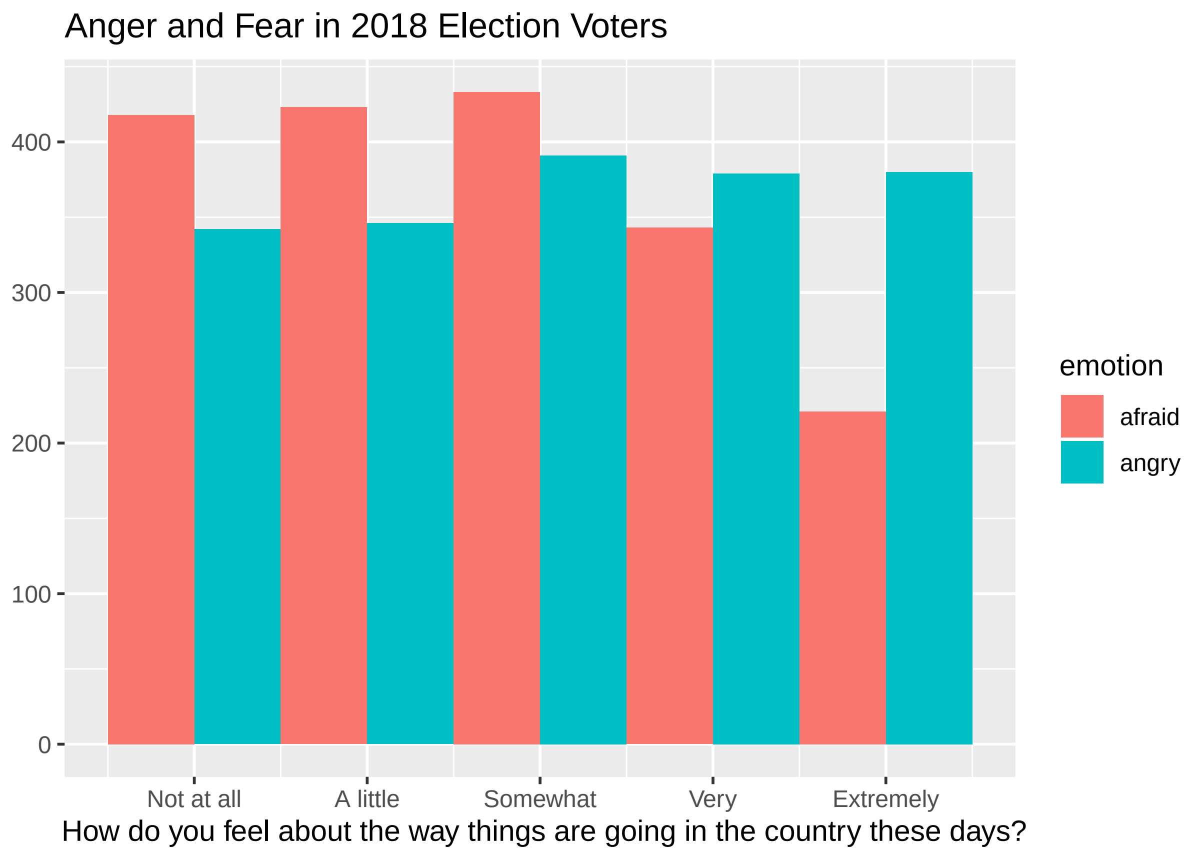
A variety of survey questions address fear and anger in respondents. Responses from the global emotion portion of the survey were examined to initially evaluate fear and anger in voters. The overall question posed was: "Generally speaking, how do you feel about the way things are going in the country these days?" 10 different emotions were surveyed on a Likert scale. Responses to two of these provide an indicator for fear and anger, though there is no way to attribute it directly to voter turnout:

- "How angry do you feel?"

- "How afraid do you feel?"

Exploratory Data Analysis.

```r
library(ggplot2)
# get all of our voters who answered both the
# angry and afraid questions
geVoters18 = voters18[which(as.numeric(voters18$geangry) >
    0 & as.numeric(voters18$geafraid) > 0), ]
# frame each variable
question4frame = data.frame(emotion = c(rep("angry",
    nrow(geVoters18)), rep("afraid", nrow(geVoters18))),
    response = c(geVoters18$geangry, geVoters18$geafraid))
# plot it
ggplot(question4frame, aes(x = question4frame$response,
    fill = emotion), stat = "count") + geom_histogram(binwidth = 1,
    position = "dodge") + scale_x_continuous(breaks = c(1,
    2, 3, 4, 5), labels = c("Not at all", "A little",
    "Somewhat", "Very", "Extremely")) + labs(title = "Anger and Fear in 2018 Election Voters",
    y = "", x = " How do you feel about the way things are going in the country these days?")
```



We can see that there seems to be more 'very' and 'extreme' responses for anger than for fear:

Outcome.

We could test our hypotheses that the responses are different for the two questions:

$$- H_0 : E(Fear) = E(Anger). - H_A : E(Fear) \neq E(Anger)$$

Testing against a null hypothesis that there is no difference between the anger responses and the fear responses shows that there is a significant difference between the two:

```r
wilcox.test(geVoters18$geangry, geVoters18$geafraid,
    alternative = "two.sided")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  geVoters18$geangry and geVoters18$geafraid
## W = 1907062, p-value = 4.586e-12
## alternative hypothesis: true location shift is not equal to 0
```

Going further, we can now test whether anger is indeed more significant than fear, or

$$- H_0 : E(Fear) \geq E(Anger). - H_A : E(Fear) < E(Anger)$$

```r
wilcox.test(geVoters18$geangry, geVoters18$geafraid,
    null = "less", alternative = "greater")
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  geVoters18$geangry and geVoters18$geafraid
## W = 1907062, p-value = 2.293e-12
## alternative hypothesis: true location shift is greater than 0
```

```r
# cohen.d(geangry ~ geafraid, data =
# geVoters18)
```

Statistical significance. This gives us a p-value = 2.293e-12 so we should reject our null hypothesis that 2018 election voters feel more fear than anger about the state of affairs in the country.

Practical significance.

5. Does household income affect how much attention reponsdents pay to politics and public affairs?

Overview.
For our self-selected question we chose to focus on whether household income affects how how closely respondents followed politics.

Operationalization.
Respondents were asked for household income using the question "Thinking back over the last year, what was your family's annual income?", this is encoded as `faminc_new`

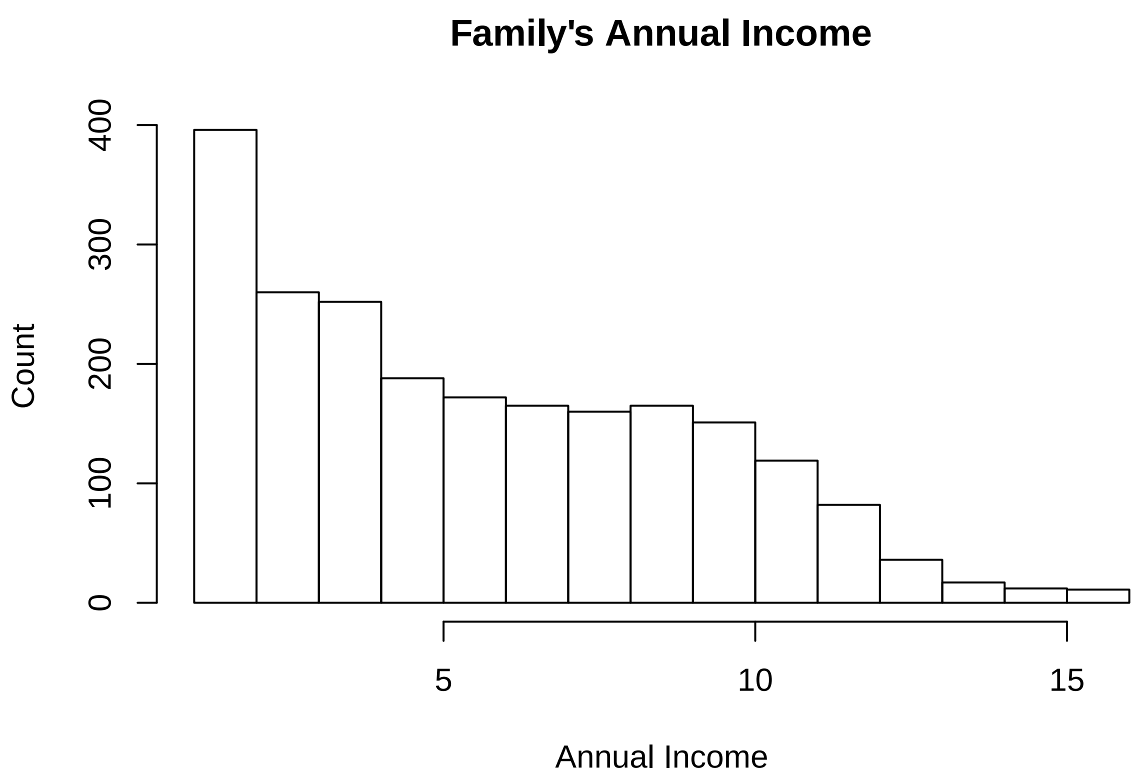
Exploratory Data Analysis.

"Decline to answer" is encoded as a 97, so we'll want to remove those rows in order to use `faminc_new`.

```
summary(anes_data$faminc_new)
```

```
##    Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    1.00    3.00    6.00   17.44   10.00   97.00
```

```
hist(anes_data$faminc_new[anes_data$faminc_new <
    20], main = "Family's Annual Income", xlab = "Annual Income",
    ylab = "Count", breaks = 20)
```




```
validWealthRespondents = anes_data[which(as.numeric(anes_data$faminc_new) >
    0 & as.numeric(anes_data$faminc_new) < 20),
    ]
```

The scale is not perfectly metric, a '3' corresponds to a family income between $20,000 and $29,000 but an 11 indicates a family income between $120,000 - $149,999.

Respondents were also asked how closely they followed politics on the following scale:

Most of the time [1] Some of the time [2] Only now and then [3] Hardly at all [4]

Analysis.

We can compare the means of our wealth respondents and our entire survey to see whether the two groups differ dramatically:

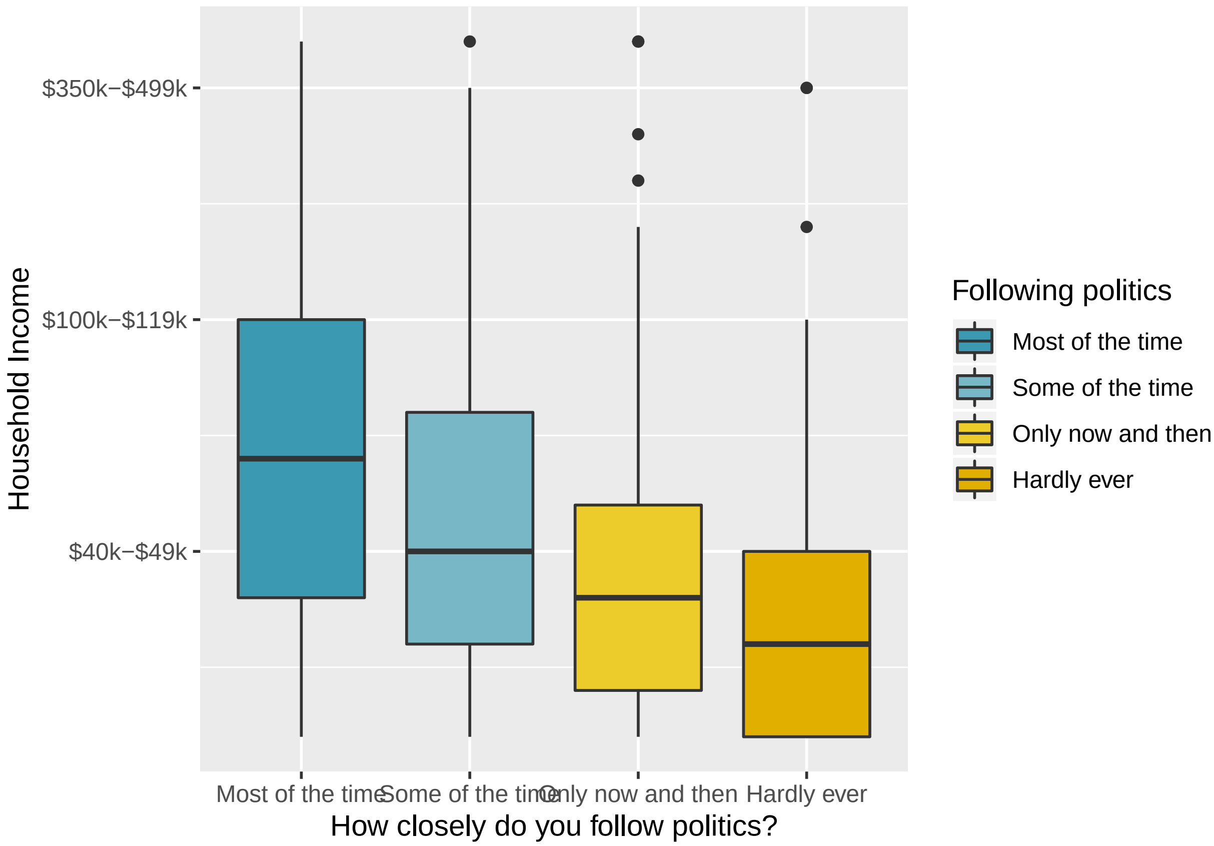
```
t.test(anes_data$follow, validWealthRespondents$follow)
```

```
##
##  Welch Two Sample t-test
##
## data:  anes_data$follow and validWealthRespondents$follow
## t = 0.48574, df = 4623.3, p-value = 0.6272
## alternative hypothesis: true difference in means is not equal to 0
## 95 percent confidence interval:
##  -0.04085737  0.06777191
## sample estimates:
## mean of x mean of y
##  1.721600  1.708143
```

This shows a p-value = 0.6272, so we cannot reject the null hypothesis that these two groups show no difference in means.

We can now begin to look at whether there is a difference in the household income levels for those who answered that the follow politics most of the time and those that answered that they hardly ever do. We get an intuition for this by graphing it:

```
library(wesanderson)
q5frame = data.frame(validWealthRespondents)
ggplot(q5frame, aes(x = factor(q5frame$follow),
    y = q5frame$faminc_new, fill = factor(q5frame$follow))) +
    geom_boxplot() + scale_fill_manual(values = wes_palette("Zissou1",
    n = 4), name = "Following politics", labels = c("Most of the time",
    "Some of the time", "Only now and then", "Hardly ever")) +
    xlab("How closely do you follow politics?") +
    scale_x_discrete(labels = c("Most of the time",
        "Some of the time", "Only now and then",
        "Hardly ever")) + scale_y_continuous(name = "Household Income",
    labels = c("$40k-$49k", "$100k-$119k", "$350k-$499k"),
    breaks = c(5, 10, 15))
```



The median family income for those who report following politics "closely"most of the time" does appear to be higher than those that report following it "hardly ever".

Since neither the family income nor the following politics responses are metric we should examine a possible relationship between these two variables using the Wilcoxon test. We'll isolate respodents who claimed to follow politics "most of the time" and those who claimed they followed politics "hardly ever" and see whether the two are different from our whole sample set.

```
activeWithWealth = validWealthRespondents[which(as.numeric(validWealthRespondents$follow) ==
    1), ]
inActiveWithWealth = validWealthRespondents[which(as.numeric(validWealthRespondents$follow) ==
    4), ]
```

First we can look at whether the wealth levels for our "most of the time" respondents differ from all of our wealth respondents:

$$- H_0 : E(Followers) = E(All). - H_A : E(Followers) \neq E(All)$$

```
wilcox.test(activeWithWealth$faminc_new, validWealthRespondents$faminc_new,
    conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  activeWithWealth$faminc_new and validWealthRespondents$faminc_new
## W = 1539600, p-value = 8.303e-16
## alternative hypothesis: true location shift is not equal to 0
## 95 percent confidence interval:
##  0.999972 1.000039
## sample estimates:
```

```
## difference in location
##                      1
```

With a p-value = 8.303e-16 this appears to be statistically significant.

Next we can look at whether the wealth levels for our "most of the time" respondents differ from all of our wealth respondents:

- $H_0 : E(Nonfollowers) = E(All)$.
- $H_A : E(Nonfollowers) \neq E(All)$

```r
wilcox.test(inActiveWithWealth$faminc_new, validWealthRespondents$faminc_new,
    conf.int = TRUE)
```

```
##
##  Wilcoxon rank sum test with continuity correction
##
## data:  inActiveWithWealth$faminc_new and validWealthRespondents$faminc_new
## W = 103508, p-value < 2.2e-16
## alternative hypothesis: true location shift is not equal to 0
## 95 percent confidence interval:
##  -2.999953 -1.999942
## sample estimates:
## difference in location
##              -2.000001
```

Outcome.
Practical significance. This also appears statistically significant, with a p-value < 2.2e-16.

Since the means of both groups differ significantly from the means of the larger population that answered the question we can explore whether there is a correlation between the family income and the self-reported following of politics:

```r
# 5 - validWealthRespondents$follow to invert
# the scale so that less interest is a 1 and
# more interest is a 4
cor(validWealthRespondents$faminc_new, 5 - validWealthRespondents$follow,
    method = "spearman")
```

```
## [1] 0.3465463
```

Practical Significance. The values for Spearman's Rank-Order Correlation, r_s, can take on the values from $+1$ to -1. r_s has the following associations:
- $+1$: perfect association of ranks
- 0: no association between the ranks
- -1: perfet negative association of ranks.

The r_s value obtained from this test was 0.35 which is a weak monotonically increasing relationship. Because of the sample size and p-value obtained, we believe that this indicates a correlation between family income of the respondents and the closeness with which they follow politics.