STAT 892 - Final Paper

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This paper outlines an experiment designed to measure how people perceive information provided in plots and whether political bias affects this perception. This experiment shows participants a mix of plots with some being political or controversial topics, while others are more general. Each plot has a control version and a deceptive version. This allows us to evaluate how an audience perceives poor or misleading graphics compared to better ones.

Introduction

Many areas of research rely on visualizations to express their findings to both experts in the field and the general public alike. This applies to other areas of life as well such as news, entertainment, and public health that reach the largest audience possible with easily-digestible visualizations and quick explanations over in-depth, domain-specific reports. (Unwin (2020)). Although this practice goes back many centuries (Friendly, Valero-Mora, and Ibanez Ulargui (2010)), in today's fast-moving, technology driven world creating visualizations has never been easier. Yet, visualizations need to be effective in order to have the desired outcome of educating the public.

A key issue in creating effective visualizations is that of bias. Sometimes bias comes from the presenter of information. Mistakes in visualizations can lead others to draw the wrong conclusions. Other times, the presenter may take advantage of an audience's trust to mislead them with purposely biased plots. Bias does not come from just the presenter though. Audience members with long-held beliefs on certain subjects may resist new information that contradicts their previous opinion.

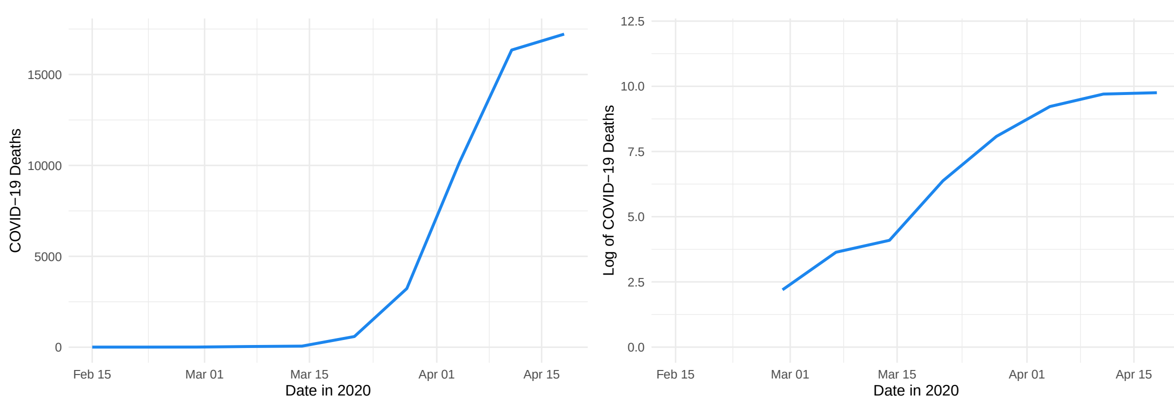
Another issue with effectively communicating through visualization is audience understanding. While good visualizations are meant to be accessible, sometimes the best way to show data can be largely unknown to the public. This diminishes the effect of the visualization.

In this paper I will propose an experiment with the intent to account for several facets of audience interactions with plots. The experiment will measure how a general audience perceives biased plots versus more neutral plots while measuring performance across different plot types and topics. The files used in the paper can be found at the project's GitHub page.

Motivation

To understand how bias can show up in creating and interpreting visualizations we first need to discuss what makes an effective visualization. In my opinion the components of effective visualizations can be grouped into two categories: accurate representations of the data and making a visualization readable for the public. The former is an ethical responsibility for a researcher since, whether intentional or not, misleading or outright false visualizations hinder the true findings of the research. The second category has many components to it. These include taking into account accessibility concerns such as avoiding plots based in red and green together and ensuring axes and labels are readable for the viewer. Note, the latter point falls into both categories.

Perhaps the greatest challenge of making effective visualizations is considering the public's graphical literacy. An example of this occurred during the first year of the COVID-19 pandemic. Many American media outlets chose to use a logarithmic scale to illustrate the total number of deaths. As seen in Figure 1, the logarithmic scale on the right does a better job of showing how the rate of deaths is changing than the linear scale on the left. However, a study by Romano et al. (2020) found on average both experienced scientists and the general public that took part in the study understand the linear scale far more than the logarithmic scale. This is likely due to a lack of experience with log functions and illustrates how choosing the plot that one feels best represents the data is not always the one an audience understands.



(a) Linear scale

(b) Logarithmic scale

Figure 1: COVID-19 deaths in the United States. Data from February 9 through April 18, 2020. Data provided by NCHS/DVS (2024).

The example above shows how the creator of a visualization can do what they believe is right and still have difficulty getting their point across due to audience misunderstanding. One element I want to look at is what types of basic visualizations do people understand best. While it seems likely the public would struggle to understand non-linear scales, knowing how pie charts compare to bar charts in terms of audience understanding would be useful.

The main focus of this experiment, however, is how the public perceives misleading visualizations compared to accurate plots. These misleading visualizations can of course be honest mistakes by the creator or publisher of the visualization, but in some cases it may be intentionally. Some of the ways this can happen include ill-fitting chart types, the y-axis not starting at zero, data being plotted incorrectly, or even exaggerated plot and axis titles. When plots exhibiting one or more of these issues are published, viewers could consider the misleading information factual, which presents many problems for society.

An example of this is in the plot below which shows the unemployment rate through the year 2011. The photo was taken from a segment aired by Fox News. This plot is misleading in two ways. First, the y-axis goes from 8% to 10%, leading to any changes in the unemployment rate from one month to another to be more pronounced. Additionally, the November percentage of 8.6%, which appears to be the lowest of the year, is instead shown to be equivalent to the previous month's percentage of 9.0%. (Leonardo (2021)).

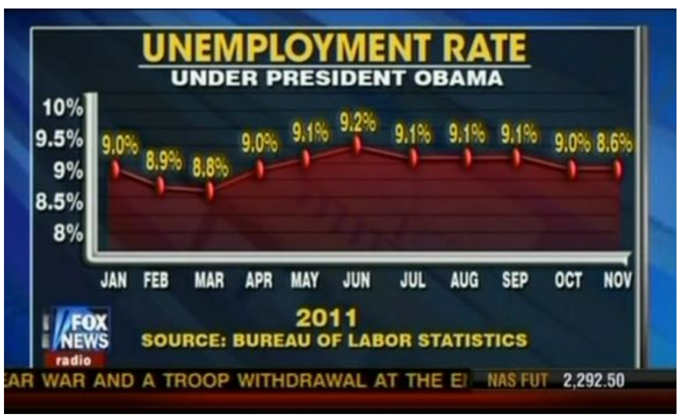


Figure 2: Plot of 2011 unemployment rate with misleading y-axis. Published by Fox News in 2011.

While this plot is not necessarily intentionally misleading, one could easily walk away with an opinion not supported by the underlying data. It is also important to keep in mind the timing and source as well. Economic issues were among the key issues Americans were concerned about following the Great Recession. This means plots that make the economic situation seem worse than it is could have negative consequences. ("Most Important Problem" (2024)). On top of this, Fox News averaged 1.87 million prime-time viewers for the year 2011, meaning many people could have been mislead at once. (Bauder (2011)).

Knowing how the public perceives misleading graphics as compared to good graphics can give researchers a way to quantify the effects of misinformation. Previous work, such as that by Lauer and O'Brien (2020) did this while controlling for the plot type. While the researchers attempted to account for potential biases from the creators of visualizations through mixing biased and unbiased plots in the experiment, they purposely avoided the other place bias can come from: the viewer. The researchers made all plots related to noncontroversial topics.

In this experiment I will account for potential audience bias by both including plot topics that are considered controversial along with noncontroversial topics and by taking demographic information from each participant. Both groups of topics will have a mix of biased and unbiased plots, as well as different types of graphs. Together, this will allow one to see how audience members with different opinions evaluate different types of graphics depending on the sensitivity of the topic and whether they can detect misleading information.

Literary Review

As previously alluded to, the main inspiration for this experiment comes from Lauer and O'Brien (2020). Their experiment showed each participant four different kinds of plots in a random order. These plots were a bar chart, a line graph, a pie chart, and a bubble graph. Each plot had a deceptive version and a nondeceptive version, called the control, based on the same data. Note, the deceptive plot used many of the tactics discussed previously in this paper. On top of the plots themselves, two titles for each topic were written, again with one being deceptive and one not. This made it so each graph type had four different possible ways to be presented. As previously mentioned, the researchers intentionally chose noncontroversial topics.

The participants were then asked a questions about their perception of each plot and provided answers on a scale from one to six. These questions focused on potential changes or differences from one state to another. This allowed for a lower score to indicate a small change, while larger scores corresponded to larger changes. After completing a question for each of the four plot types, participants were then asked to rank the graphs from easiest to hardest to understand and finally state how comfortable they were with each plot type through multiple choice questions.

In total, the experiment had 329 participants. These participants were either first-year students in psychology classes at Arizona State University or instructors in similar fields at different universities. While this was convenient for the researchers, it is unlikely this group is representative of the population at large, since all participants are either college students or faculty.

The results of the plot interpretation are shown in Figure 3. (Lauer and O'Brien (2020), pg.333). In each plot type, the largest average scores, which again indicate the greater perceived change from one state to another, come from the deceptive plots. This gap is somewhat pronounced in all plot types except the bubble graphs. Meanwhile, exaggerated plot titles seem to have played far less of a role in participant answers. This could suggest that viewers are better equipped to disregard poor headlines than poor graphs.

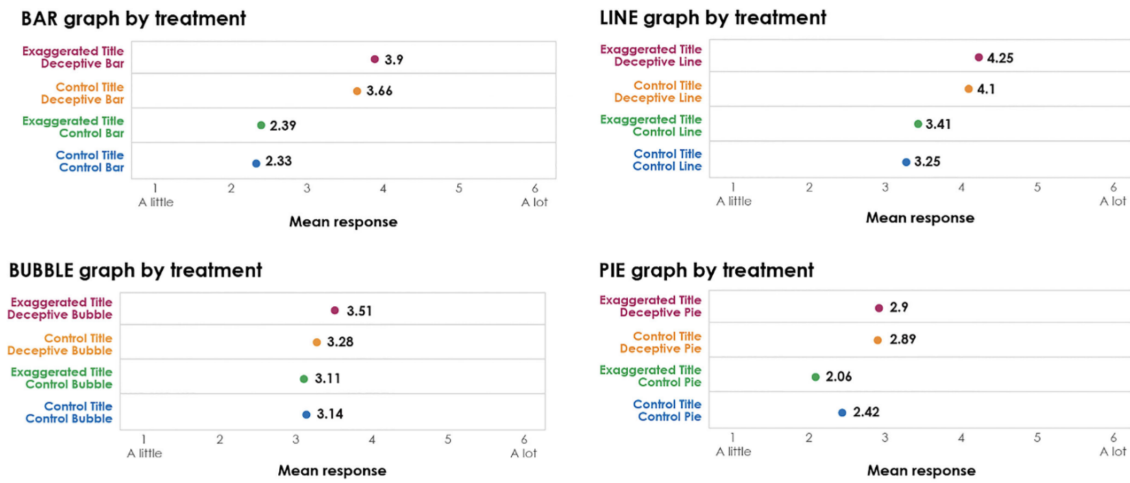


Figure 3: Mean responses to graphs in the experiment by Lauer and O'Brien (2020).

While attempting to replicate the title effect would be interesting, for this experiment I will not be focusing on plot titles. In its place, each plot type will have a deceptive and control plot related to a controversial topic with a neutral headline for all plots. This is what I believe the experiment by Lauer and O'Brien (2020) is lacking in regards to my own research interests of the role bias plays in the perception of visualizations. Additionally, I will not be evaluating the audience's perception of bubble plots. Instead I will focus on the other three types.

For a better understanding of how to conduct an experiment that measured bias I considered a study by Schwalbe et al. (2024). The study was focused on how American individuals from different backgrounds perceive headlines and corresponding articles. Half of the articles were nonpolitical while the other half were all related to Donald Trump. These articles were graded on a scale from against to for Trump. The participants were shown an equal number of each. The articles were also real news, fake news, and a mix of both in equal numbers.

Participants were asked questions about the articles. These included whether the article was truthful and if they would share it with others. These answers taken on a five-point scale ranging from negative to positive. At the end of the study participants were asked several demographic questions, including their opinions of Donald Trump on a seven-point scale. On this scale a one implied strong opposition, a four was neutral, and a seven was strong support. Researchers chose to combine participants with scores of one to three in one group, five to seven in another, and leave scores of four as their own category.

For the articles involving Trump, researchers labeled cases concordant when the article skew matched the participants beliefs and discordant when they did not. Researchers used these labels along with participant answers to generate a political bias score. The results of this metric highlight the importance of this research as the authors found real news was more effected by bias than fake news.

Participants were recruited through a platform called Lucid. The service used quota sampling based off demographic targets to find participants on multiple websites. Researchers used quota sampling to ensure their sample reflected the U.S. Census for many demographic variables. 2,180 participants were recruited, though 371 were excluded for failing to follow survey rules or missing attention checks built into the survey.

While this study focused on articles instead of visualizations, it shows ways of measuring bias that I believe could be applied to a graphics study. Additionally, quota sampling presents an interesting approach to building a sample.

Experimental Methods

Sets of Plots

The survey used in this experiment will consist of two sets of plots: one set related to non-controversial topics and one for controversial topics. For simplicity the controversial topics will be related to politics, health, or the environment. Specifically, the topics will be chosen if they tend to be interpreted differently based on one's position on the left-right political spectrum. The noncontroversial set will focus on topics less likely to fit onto this spectrum. The topics in both sets should be based in the country of the participants in an attempt to mimic a visualization they could see in their daily lives. For the purpose of this paper we can assume the participants are all living in the United States.

Noncontroversial	Controversial
Movies from a particular studio in a year	Changes in unemployment rate
Graduation rates at public universities	Government spending
Ticket sales of minor league baseball team	Changes in average temperatures over time
Adoption rates at a pet shelter	Gun deaths in a major city

Figure 4: Potential topics used for generating plots sorted into the sets outlined in the paper.

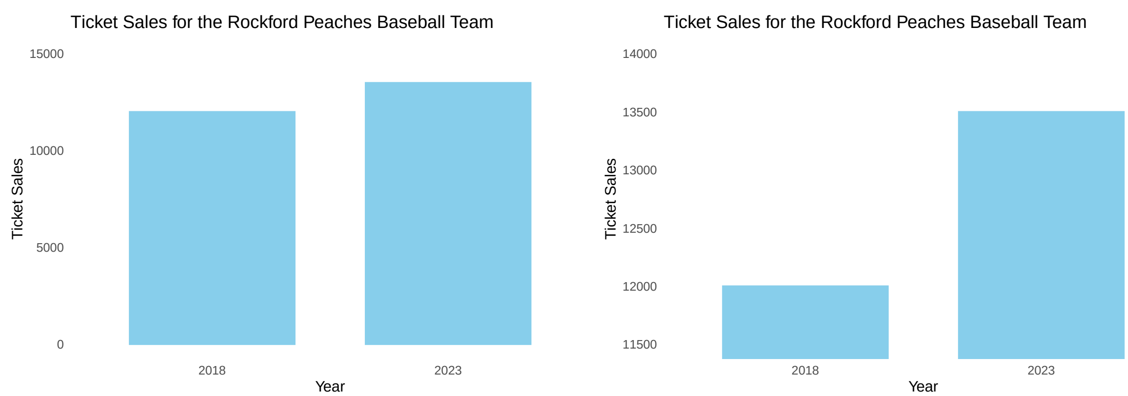
Some examples of potential topics are shown in Figure 4. Plots related minor league baseball teams and pet adoptions in a random U.S. town are unlikely to come with the prior biases that accompany climate change or gun violence visualizations. One key point related to some of the controversial topics is timing. In terms of where answers fall on a political spectrum, opinions on a statistic like the unemployment rate change based on who is in power. This implies that the survey portion of the experiment should not take place between a national election and the inauguration of any new president or congress.

Within each set there will be two cases of each plot type, each with a control and deceptive version. In the controversial set, one case will be on a topic that left-leaning individuals likely feel passionate about and the other will be the same for right-leaning individuals. For example one case may involve the increase of debt over the term of a Republican president and another may involve abortions performed by Planned Parenthood. Left-leaning individuals biases may make them more likely to believe the deceptive plot that exaggerates the debt in the former example, while the same can be said for right-leaning participants in the latter case.

Plot Types

For this experiment, participants will be shown three types of graphs. These will be bar charts, line plots, and pie charts. Each chart type will appear once per set in a random order. As was the case in the experiment by Lauer and O'Brien (2020), each plot will have a control version and a deceptive version. The version shown to the audience will be decided through randomization.

The control and deceptive plots must follow certain guidelines. For bar charts, the control graphs must have an equal width for each bar and an axis that starts at zero. While there are many ways to make a deceptive bar chart, this experiment will focus on a y-axis starting at some number other than zero. Figure 5 shows the ticket sales for a fictional minor league baseball team in 2018 and 2023. In the control plot, the y-axis starts at zero and goes to \$15,000, which is more than the amount in either year. The y-axis of the deceptive plot not only starts at \$11,000, but also stops at \$14,000. Visually this suggests the ticket sales increased by a factor of three or four instead of the 12.5% increase that actually occurred.

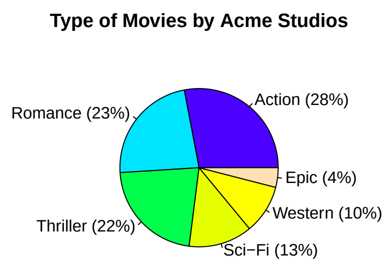


(a) Control (b) Deceptive

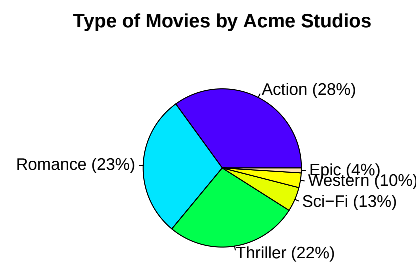
Figure 5: Example of a bar chart for ticket sales of a fictional baseball team in 2018 and 2023..

The line plots will follow the same guideline as the bar graphs. Control plots will start have the y-axis beginning at zero while deceptive plots will have an altered y-axis to make changes from one time point to another seem larger. An example of the deceptive plot can be found in Figure 2, while Figure 7 shown later on is a control plot. Note, the data points will be plotted correctly for all line plots, unlike in Figure 2.

Pie charts on the other hand will manipulate the data from the control plots to create the corresponding deceptive plots. This is to achieve the effect of making sections of the pie chart bigger or smaller than they should be. Figure 6 shows an example of this. Here the breakdown of movies by genre made by a movie studio is shown. In the control plot, the size of the "pie slices" correspond to the percentage listed next to the genre. The deceptive plot claims to follow the same percentages but increases the size of the action, romance, thriller slices while decreasing the other genres relative to their actual percentage.



(a) Control



(b) Deceptive

Figure 6: Example of a pie chart related to the distribution of movies by genre for a fictional movie studio.

The complete sets of both controversial and noncontroversial plots can be found at Plots-for-Experiment.pdf.

Plot Questions

Questions about each plot will follow the format from Lauer and O'Brien (2020) where each participant will be asked to compare the difference or change from one state to another. For the pie charts shown in Figure 6 this would be asking how many more romance movies were made than westerns. For bar charts and line plots questions would follow the format in Figure 7. This figure shows how a control line plot from the noncontroversial set would be presented. The participant is then asked how much change occurred from one time point to another.

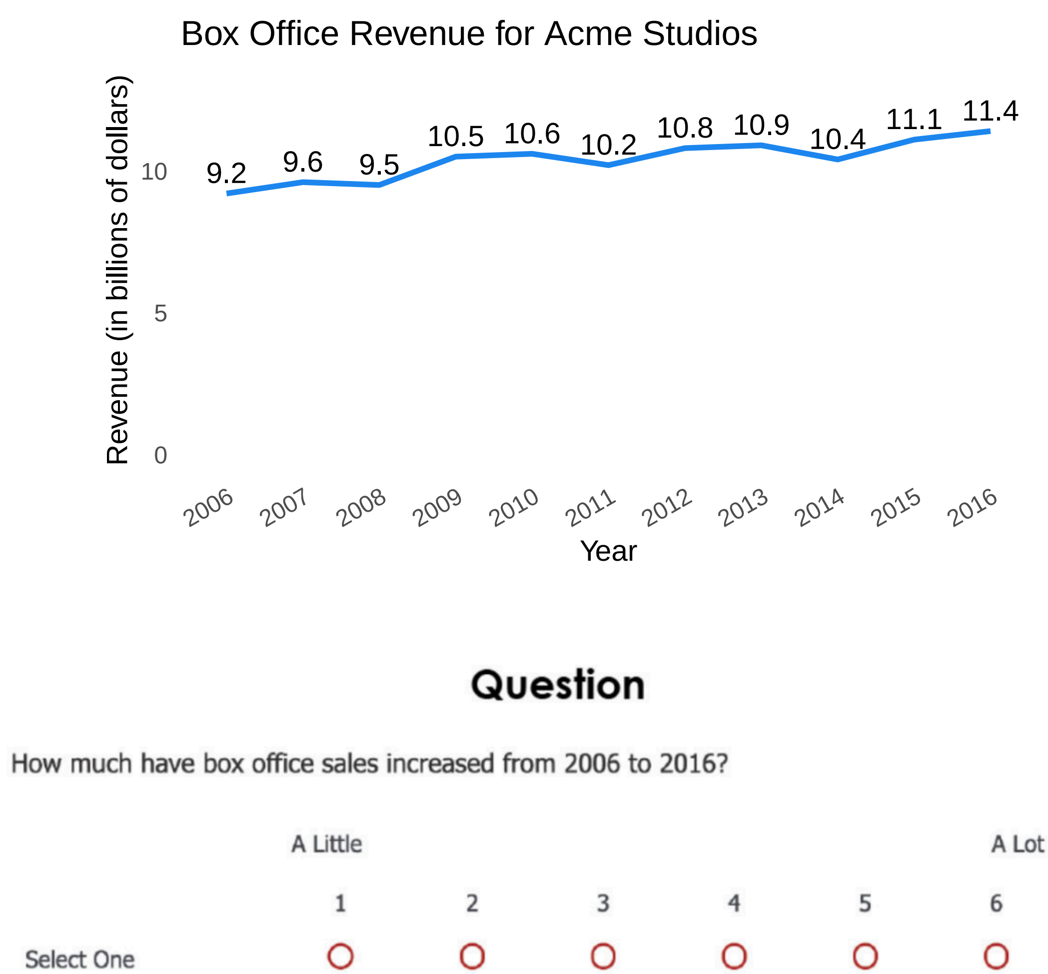


Figure 7: Line plot example with a corresponding question. (Lauer and O'Brien (2020), pg. 331)

After completing the perception question for each plot, participants will be asked to rate the three types of plots in order of preference. Examples of noncontroversial control plots will be shown in case they are still unfamiliar with the names of the plot types after completing the majority of the survey.

Previously it was said each of the two sets would have two graphs for each plot type. Since there are three plot types there will be a total of 12 plots shown and as many questions related to plots on the survey. Each question has a control and deceptive plot, so one version will be chosen at random. Instead of showing all of the noncontroversial plots and then all controversial ones, all twelve plots will be shown in a random order. Grouping the questions into sets is purely for the purpose of analyzing the data.

Demographic Questions

Before completing the survey participants will be asked to fill out a demographic questionnaire. The demographic variables will include gender, race, age group, region, income, education level, political leaning, and whether they voted in the most recent election. The question on their political leaning will try to capture a participant's feeling on where their opinions generally fall on the political spectrum. The answers will be on a seven-point scale similar to the one by Schwalbe et al. (2024), except answers of less than or greater than four will correspond to a left or right political position respectively. This will be used to measure bias when evaluating plots belonging to the controversial set.

The reason for including demographic information at the end of the survey instead of the beginning is related to the political leaning question. If participants were asked this question prior to evaluating any plots, they may become aware of the survey's intent and answer questions differently than they otherwise would have. By asking demographic questions at the end of the survey the participants are more likely to provide genuine answers.

Note, all demographic questions and answer banks will be written with accessibility in mind. Many questions will provide options for unlisted answers and a box for those who prefer not to answer. This includes the political question. While this question specifically could hinder the analysis in some ways, it way also allow us to evaluate apolitical participants along with those who fall on the traditional political spectrum.

Attention Checks

This survey will be conducted online. To ensure participants are actively taking the survey, attention check questions will be used. An example from Rosenzweig, Edelman, and Moss (2020) is shown in Figure 8. The question tells the participant which answer to select and hopefully filters out any participants that are simply selecting answers without reading the questions or evaluating the plots.

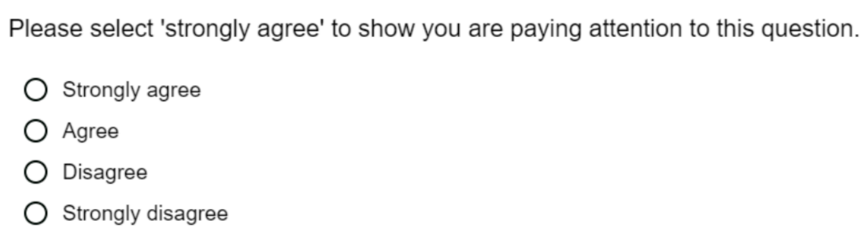


Figure 8: Example of an attention check. (Rosenzweig, Edelman, and Moss (2020)).

Note, the format and timing of the attention checks are still non finalized. Including unused plots with the checks may increase the odds of catching those who are not reading the questions. Similarly, answers may be formatted to follow the number scale shown in Figure 7.

Data Collection

The administering the survey will be done online. This allows us to consider participants from all over the country and not just those in the Lincoln, NE area. The questions will be given via a *Shiny* application in the R programming language. (Chang et al. (2024)). More specifically, the `shinysurveys` package will be used. While I have not been able to implement the survey yet, Figure 9 provides a look at what the application can produce. (Wyckoff (2018)). The sliding scale on the left side would work well for the questions about the plots, and integrating plots from base R and `ggplot2` is possible. (Wickham (2016)).

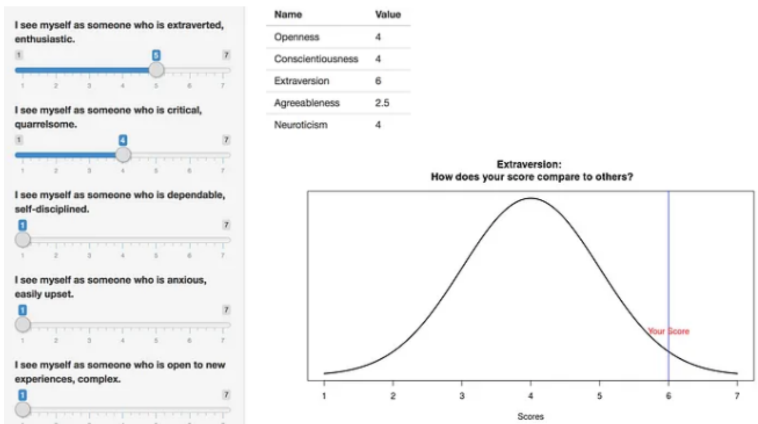


Figure 9: Example of shiny output from Wyckoff (2018).

The first wave of participants will be recruited through Amazon Mechanical Turk (MTurk). MTurk is a crowd-sourcing marketplace that will find participants to take the survey. ("MTURK Tip Sheet for Researchers" (2022)). The number of desired participants is unknown at this point, though I imagine it should be at least a few hundred. This will hopefully produce a diverse pool of participants. A second wave of participants will be recruited if too few people have taken the survey or the demographics of the first wave is not representative in any way. Quota sampling may be used in this event but will not be used for the first wave.

The data returned from the experiment will need to have several variables besides the answers given by the participant. The order of the plots for an individual participant will not be tracked since each person will see all 12 plots. However, the version of each plot will be tracked. Ideally, for each plot about half of the participants will see the control version and the other half will see the deceptive version. Additionally each plot will be marked based on which set it comes from. Furthermore, plots from the controversial set will need a variable to say whether they are designed to incite an overestimation from either left-leaning or right-leaning participants.

The demographic questions will be more straightforward in that only the answers given by the participant will be taken. For the question that asks participants to rank the three plot types, three variables will be created to represent each type and store the placement that type was given. The data will also need to include results of the attention checks.

Analysis Plan

Once the data is collected there will be several steps to the analysis. Much of it will be similar to the analysis methods used by Lauer and O'Brien (2020). Specifically, the plot in Figure 3 provides a nice template for seeing the differences among the groups. For this experiment we could compare the mean values of the two versions of plots while controlling for the set for each plot type. This could be an early indication if there is a bias effect, but we would also need to consider the variance for each group as it is possible the controversial plots have a wider range of answers. This could mean showing a visualization off the distributions for each option mentioned above.

For measuring political bias we are first going to repeat what Schwalbe et al. (2024) and condense the political leaning answers. The participants will be given answers on a seven-point scale, but we will set all answers less than four to "left", equal to four as "neutral", and greater than four to "right". All participants that opted out of this question will be given the label "other". With this new categorical variable we can create a similar series of plots to the ones discussed previously that allow us to see if there are any difference in the answers provided for the plot questions based on political leanings. This includes seeing whether one group is more susceptible to deceptive plots.

Another element of the analysis could be matching political leanings to the controversial set of plots. For each participant we could set plots that have the same label as theirs to "concordant" as Schwalbe et al. (2024) did. In cases of disagreement we could use discordant, while all other participants could be given an other category. This would be another way to see how bias affects perception as it would show if people overestimate effects they want or believe to be true, regardless of political position. Keeping in line with was was just discussed, seeing the performance of people who voted in the last election versus those who did not could be interesting as well.

The question regarding which plots people prefer will be analysed as well. While there is research into how the public perceives the plot types already, this could add to it and help creators of visualizations in the future.

I believe the dataset produced from this experiment would have other ways to be analyzed as well. Unfortunately I was unable to simulate a dataset to demonstrate some of the plots discussed above. Additionally, I did not mention any ways model fitting could be used for analysis either. I may add this in the future.

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Appendix A: R Code

```
# Add all necessary libraries
library(ggplot2)
library(dplyr)
library(knitr)
library(kableExtra)

# Datasets used
covid <- read.csv("2020 US Covid Deaths.csv")

# Code for Plots
covid$End.Date <- as.Date(covid$End.Date, format = "%m/%d/%Y")

covid_filtered <- covid %>%
  filter(End.Date >= "2020-02-09") %>%
  filter(End.Date <= "2020-04-18")

covid_filtered2 <- covid_filtered %>%
  mutate(COVID.19.Deaths = if_else(End.Date < "2020-02-29",
                                   NA, COVID.19.Deaths))

ggplot(covid_filtered, aes(x = End.Date, y = COVID.19.Deaths)) +
  geom_line(color = "dodgerblue2", size = 1) + # Line properties
  labs(
    x = "Date in 2020",
    y = "COVID-19 Deaths"
  ) +
  theme_minimal()

ggplot(covid_filtered2, aes(x = End.Date, y = log(COVID.19.Deaths))) +
  geom_line(color = "dodgerblue2", size = 1) + # Line properties
  labs(
    x = "Date in 2020",
    y = "Log of COVID-19 Deaths"
  ) +
  ylim(0, 12) +
  theme_minimal()

topics <- data.frame(
  Noncontroversial = c("Movies from a particular studio in a year",
```

```
                       "Graduation rates at public universities",
                       "Ticket sales of  minor league baseball team",
                       "Adoption rates at a pet shelter"),
  Controversial = c("Changes in unemployment rate",
                    "Government spending",
                    "Changes in average temperatures over time",
                    "Gun deaths in a major city")
)

kable(topics)


RubberDucks <- data.frame(
  Year = c("2018", "2023"),
  Sales = c(12000, 13500)
)

ggplot(RubberDucks, aes(x = Year, y = Sales)) +
  geom_bar(stat = "identity", color = "skyblue", fill = "skyblue",
           width = 0.7) + coord_cartesian(ylim = c(0, 15000)) +
  labs(title = "Ticket Sales for the Rockford Peaches Baseball Team",
       x = "Year",
       y = "Ticket Sales") +
  theme_minimal() + theme(panel.grid = element_blank())

ggplot(RubberDucks, aes(x = Year, y = Sales)) +
  geom_bar(stat = "identity", color = "skyblue", fill = "skyblue",
           width=0.7) + coord_cartesian(ylim = c(11500, 14000)) +
  labs(title = "Ticket Sales for the Rockford Peaches Baseball Team",
       x = "Year",
       y = "Ticket Sales") +
  theme_minimal() + theme(panel.grid = element_blank())


control_movies <- data.frame(
  Genre = c("Action",
            "Romance",
            "Thriller",
            "Sci-Fi",
            "Western",
            "Epic"),
  Percentage = c(28, 23, 22,
```

```r
                 13, 10, 4)
)

deceptive_movies <- data.frame(
  Genre = c("Action",
            "Romance",
            "Thriller",
            "Sci-Fi",
            "Western",
            "Epic"),
  Percentage = c(35, 29, 27,
                 5, 3, 1)
)

pie(control_movies$Percentage,
    labels = paste(control_movies$Genre,
                   " (", control_movies$Percentage, "%)", sep = ""),
    main = "Type of Movies by Acme Studios",
    col = topo.colors(nrow(control_movies)))

pie(deceptive_movies$Percentage,
    labels = paste(deceptive_movies$Genre,
                   " (", control_movies$Percentage, "%)", sep = ""),
    main = "Type of Movies by Acme Studios",
    col = topo.colors(nrow(deceptive_movies)))


box_office <- data.frame(
  Year = c("2006", "2007",
           "2008", "2009",
           "2010", "2011",
           "2012", "2013",
           "2014", "2015", "2016"),
  Dollars = c(9.2, 9.6,
              9.5, 10.5,
              10.6, 10.2,
              10.8, 10.9,
              10.4, 11.1,
              11.4)
)

ggplot(box_office, aes(x = Year, y = Dollars, group = 1)) +
```

```
  geom_line(color = "dodgerblue2", size = 1) +
  geom_text(aes(label = Dollars),
            vjust = -0.5, size = 4, color = "black") +
  labs(title = "Box Office Revenue for Acme Studios",
       x = "Year",
       y = "Revenue (in billions of dollars)") +
  theme_minimal() +
  theme(axis.text.x = element_text(angle = 30, hjust = 1)) +
  ylim(0, 13) +
  theme(panel.grid = element_blank())

# Attempt at simulating a dataset.
n <- 300
```

Appendix B: AI Prompts and Answers

Used responses

Prompt: What color options do I have for this pie chart? (code was copied to prompt but I chose not to include it here)

Answer: You can use built-in color palettes like `rainbow`, `heat.colors`, `terrain.colors`, or `topo.colors`

Prompt: Can you make a `ggplot2` line graph with this? (I gave it my code with a data frame)

Answer: Code returned:

```
ggplot(box_office, aes(x = Year, y = Dollars, group = 1)) +
  geom_line(color = "blue", size = 1) +  # Line settings
  geom_point(color = "red", size = 2) +  # Add points for emphasis
  labs(title = "Box Office Revenue Over Years",
       x = "Year",
       y = "Revenue (in billions)") +
  theme_minimal() +  # Clean theme
  theme(axis.text.x = element_text(angle = 45, hjust = 1))
# Rotate x-axis labels
```

Follow-Up Question: Instead of red points can I print the value of each number?

Updated Answer: replace

```
geom_point(color = "red", size = 2)
```

with

```
geom_text(aes(label = Dollars), vjust = -0.5, size = 3, color = "black")
```

in previous code.

Unused Responses

Prompt: I want to simulate a data set. The first variable is a participant ID which can just be integers in order. The second should be either deceptive or control with a 50-50 shot for either. The third variable should be an integer from 1 to 6 with a mean of 2.39. How would I make this in R?

Answer: Code returned:

```r
n_participants <- 100  # Adjust this number as needed

# Create a participant ID column
Participant_ID <- 1:n_participants

# Generate the second variable: "Deceptive" or "Control" with a 50-50 chance
Condition <- sample(c("Deceptive", "Control"),
                    size = n_participants, replace = TRUE)


# Define the target probabilities to achieve a mean of 2.39
# Probabilities are set based on their contribution to the mean
# These weights were calculated to give a mean close to 2.39
probabilities <- c(0.45, 0.20, 0.15, 0.10, 0.05, 0.05)

# Generate the variable
Random_Integer <- sample(1:6, size = n_participants, replace = TRUE,
                         prob = probabilities)

# Combine into a data frame
simulated_data <- data.frame(
  Participant_ID = Participant_ID,
  Condition = Condition,
  Random_Integer = Random_Integer
)
```

Prompt: Given this code (code not included here - see Figure 8 in Plots-for-Experiment.pdf) how do I make a shiny application that asks “How much did the global temperature rise from 1950 to 2020?”

Answer: Code Returned (Did not run)

```r
library(shiny)
library(ggplot2)
```

```r
# Data
temp <- data.frame(
  year = c("1950", "1960", "1970", "1980", "1990", "2000", "2010", "2020"),
  temp = c(51.6, 51.9, 51.6, 52.8, 53.4, 53.7, 52.7, 55.7)
)

# UI
ui <- fluidPage(
  titlePanel("Global Temperature Rise from 1950 to 2020"),
  sidebarLayout(
    sidebarPanel(
      p("Question: How much did the global temperature rise from
        1950 to 2020?"),
      actionButton("show_answer", "Show Answer")
    ),
    mainPanel(
      plotOutput("tempPlot"),
      uiOutput("answer")
    )
  )
)

# Server
server <- function(input, output) {
  output$tempPlot <- renderPlot({
    ggplot(temp, aes(x = year, y = temp, group = 1)) +
      geom_line(color = "maroon", size = 1) +
      geom_text(aes(label = temp),
                vjust = -0.5, size = 4, color = "black") +
      labs(title = "Average Yearly Temperature",
           x = "Year",
           y = "Temperature (Fahrenheit)") +
      theme_minimal() +
      theme(axis.text.x = element_text(angle = 30, hjust = 1)) +
      ylim(50, 56) +
      theme(panel.grid = element_blank())
  })

  output$answer <- renderUI({
    req(input$show_answer)  # Wait for button click
    temp_rise <- temp$temp[temp$year == "2020"]
    - temp$temp[temp$year == "1950"]
```

```r
    tagList(
      h4("Answer:"),
      p(sprintf("The global temperature rose by %.1f°F
                from 1950 to 2020.", temp_rise))
    )
  })
}

# Run the application
shinyApp(ui = ui, server = server)
```