Figure Assignment (COGS219)

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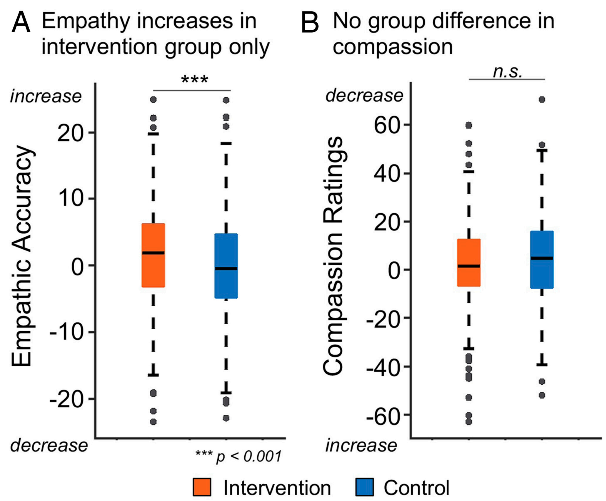
Original Study

- Link
  - paper: Film intervention increases empathic understanding of formerly incarcerated people and support for criminal justice reform
  - data and code: https://osf.io/eugjd/
- Introduction:
  - This study investigated whether watching a movie about prison and justice could significantly improve people's empathy and compassion toward the formerly incarcerated. During the study, participants completed the task in which they watched videos of individuals sharing their emotional life stories and rated the storyteller's emotions at each moment across two visits. The storytellers in the videos were all formerly incarcerated individuals, but they were presented to participants with a randomized label—either "student" or "formerly incarcerated." Between the two visits, participants were assigned to watch one films: either Just Mercy, a movie about a lawyer fighting for justice for an innocent man sentenced to death, or other control movies. Therefore, the primary question was whether the storyteller's label and the type of movie viewed between visits influence participants' empathic inference accuracy and compassion.
- Main figure: fig 1 from the paper

```r
knitr::include_graphics("paper/fig01.jpg")
```



- Explanation:
  - The original caption from the paper: 'Changes in empathic accuracy and compassion toward formerly incarcerated storytellers after film intervention. (*A*) Empathic accuracy increases in the intervention group only. Participants in the intervention group (N = 327), relative to the control group (N = 382), demonstrated an increase in their ability to accurately infer the feelings of formerly incarcerated people during the empathic accuracy task after watching the film ($P < 0.001$). Empathic accuracy was measured by taking the RMSE between participant inference ratings and the storyteller's self-ratings. Plotted are average (post–pre) change scores in RMSE for video trails where storytellers were labeled "formerly incarcerated." For plotting purposes, we inverted the RMSE change scores so that positive values indicate greater accuracy. (*B*) No change in compassion. There are no group differences in the change in compassion for formerly incarcerated storytellers. Plotted are average (post–pre) change scores in compassion for video trials where storytellers were labeled "formerly incarcerated." Bars indicate the two groups (intervention and control). All data are represented in box plots where the median is a black line and the upper and lower "whiskers" represent the bounds of the quartiles.'
- Strengths
  - Has provided the essential information about the main result: the plot has shown and compared the average rating changes across two visits in each condition (with or without intervention). It has also shown whether there are significant difference between two conditions. This is sufficient for the readers to capture the main conclusion.
- Weakness

* Not showing the distribution: it is not clear what is the distribution of rating change
* Not color-blindness or black-and-white printing friendly: the plot uses the default blue and orange color in matlab, which is not the optimal choices in many cases
* Confusing labels: the y label is 'empathic accuracy' and 'compassion ratings', but according to their paper these are actually the difference of these values across two visits, which are quite different.
* The overall balance of size of different components and the layout is not pretty. (this is very subjective)
* The author has their own concern for flipping 'increase' and 'decrease' for the compassion plot, but it only makes the plot less intuitive to the readers.
* The zero line could be further stressed so that it will be easier to tell whether the values are increasing (above 0) or decreasing (below 0).

Reproduction of Main Figures

Dara Preprocessing

While the authors have provided the preprocessed data for further analysis in R, here we started with the raw data to examine whether their data are processed correctly. (Since the raw empathy inference response are not provided, we will use directly used the accuracy metrics (Pearson correlation score and RMSE) provided by the authors).

```r
library(tidyverse)

data_path <- 'data/N709_EmpathicAccuracyTaskDat.csv'
loaded <- read.csv(data_path)
```

```r
# get rid of redundant columns
cleared_loaded <- loaded |>
  select(obsID, movie, gender, age, obsRace, Ideology, SES,
         stimID, stimRace, storyteller_label_attn_check, cond, visit,
         EAcorr, EArmse, compassion, RemoveMisLabeled1)

# remove those with missing data
cleared_loaded <- cleared_loaded |>
  filter(!RemoveMisLabeled1)
```

```r
cleared_loaded <- cleared_loaded |>
  select(-RemoveMisLabeled1)
```

Separate the subject's empathy data and other data

```r
subject_info <- cleared_loaded |>
  select(obsID, movie, gender, age, obsRace, Ideology, SES) |>
  distinct(obsID, .keep_all = TRUE)

survey_data <- cleared_loaded |>
  select(
    obsID, stimID, storyteller_label_attn_check,
    cond, visit, EAcorr, EArmse, compassion)

head(subject_info)
```

```
  obsID      movie gender age obsRace     Ideology SES
1   271  Moneyball  woman  29   White      Liberal   8
2   274 Concussion    man  50   White      Liberal NaN
3   276  Moneyball    man  65   White   OtherRight   6
4   284 Just Mercy  woman  49   White      Liberal NaN
5   286 Concussion  woman  64   White      Liberal   2
6   289 Just Mercy    man  56   Asian Conservative   3
```

Compute each subjects' average inference accuracy and compassion in two visits

```r
empathy_collapsed <- survey_data |>
  drop_na() |>
  group_by(obsID, visit, storyteller_label_attn_check) |>
  summarize (
    compassion = mean(compassion, na.rm=TRUE),
    EAcorr=mean(EAcorr, na.rm=TRUE),
    EArmse=mean(EArmse, na.rm=TRUE)
  ) |> ungroup()
```

```
`summarise()` has grouped output by 'obsID', 'visit'. You can override using
the `.groups` argument.
```

```r
# leave out those who do not have both types of story-teller in both visits
# i.e. visit 1/2 x story-telley prisonser/student
empathy_collapsed <- empathy_collapsed |>
  group_by(obsID) |>
  filter(n() == 4)  |>
  ungroup()

nrow(empathy_collapsed)
```

```
[1] 2668
```

```r
head(empathy_collapsed)
```

```
# A tibble: 6 x 6
  obsID visit storyteller_label_attn_check compassion  EAcorr EArmse
  <int> <int> <chr>                             <dbl>   <dbl>  <dbl>
1   271     1 Formerly Incarcerated              86.8  0.626    17.7
2   271     1 Student                            94.2  0.354    25.2
3   271     2 Formerly Incarcerated              88.3  0.138    29.2
4   271     2 Student                            92.8  0.461    26.2
5   273     1 Formerly Incarcerated              56.7  0.645    17.0
6   273     1 Student                            43   -0.0404   29.2
```

Fitting

Examine how the interaction between time point (i.e. 'visit'), the condition (i.e. 'cond', what type movie people watch between two surveys) and label (i.e. whether the story teller is labeled as 'formerly incarcerated' or 'student') affect RMSE score (as in the original paper). Here we closely follow how the original study code categorical data.

```r
library(lmerTest)
library(broom.mixed)

# combine all info, and rename some columns to prepare for fititng
fitting_table <- subject_info |>
  inner_join(empathy_collapsed, by='obsID') |>
  mutate(visit = case_when(
    visit == 1 ~ "pre",
    visit == 2 ~ "post",
  )) |>
```

```r
  mutate(
    cond = if_else(movie == "Just Mercy", "intervention", "control")
  ) |>
  rename(storyteller_label=storyteller_label_attn_check)

# remove any with nan
fitting_table <- fitting_table |>
  drop_na()

# further clean up (e.g. some of more than one race --> more)
possible_races <- c(
  "White", "Asian", "Hispanic or Latino",
  "Black or African American", "Native")
fitting_table <- fitting_table |>
  mutate(
    obsRace = if_else(obsRace %in% possible_races, obsRace, "More")
  ) |>
  mutate(
    gender = if_else(gender == "nonbinary", "other", gender)
  )

# convert some columns to categories
cols_to_factorize <- c(
  "obsID", "gender", "obsRace", "Ideology", "SES")
fitting_table <- fitting_table |>
  mutate(across(all_of(cols_to_factorize), as.factor)) |>
  mutate(cond=factor(cond, levels=c("control", "intervention"))) |>
  mutate(visit=factor(visit, levels=c("pre", "post"))) |>
  mutate(
    storyteller_label=factor(
      storyteller_label, levels=c("Student", "Formerly Incarcerated")))

# apply contrasts
contrasts(fitting_table$cond) = contr.poly(2)
contrasts(fitting_table$visit) = contr.poly(2)
contrasts(fitting_table$storyteller_label) = contr.poly(2)
contrasts(fitting_table$obsRace) = contr.poly(6)
contrasts(fitting_table$gender) = contr.poly(3)
contrasts(fitting_table$Ideology) = contr.poly(4)
contrasts(fitting_table$SES) = contr.poly(10)

# fit full lme model ()
```

```r
rmse_fit_model <- lmer(
  EArmse ~ cond* storyteller_label * visit
  + (1|obsID) + obsRace + gender + Ideology + SES,
  data=fitting_table)
rmse_fit_result <- tidy(rmse_fit_model, effects = "fixed", conf.int = TRUE)
```

```r
rmse_fit_result |> mutate(across(where(is.double), ~round(., 4)))
```

```
# A tibble: 27 x 9
   effect term     estimate std.error statistic    df p.value conf.low conf.high
   <chr>  <chr>       <dbl>     <dbl>     <dbl> <dbl>   <dbl>    <dbl>     <dbl>
 1 fixed  (Interc~   27.6       1.02      27.0    580  0         25.6     29.7
 2 fixed  cond.L     -0.597     0.295     -2.03   580  0.0432    -1.18    -0.0182
 3 fixed  storyte~   -0.338     0.164     -2.06  1797  0.0392    -0.660   -0.0167
 4 fixed  visit.L    -0.515     0.164     -3.14  1797  0.0017    -0.837   -0.194
 5 fixed  obsRace~    3.42      1.94       1.76   580  0.0784    -0.389    7.22
 6 fixed  obsRace~   -1.50      0.863     -1.73   580  0.0837    -3.19     0.2
 7 fixed  obsRace~   -6.42      2.73      -2.35   580  0.019    -11.8     -1.06
 8 fixed  obsRace~   -7.79      2.96      -2.63   580  0.0087   -13.6     -1.98
 9 fixed  obsRace~   -4.39      1.75      -2.51   580  0.0124    -7.84    -0.953
10 fixed  gender.L   -0.628     0.304     -2.06   580  0.0397    -1.23    -0.0298
# i 17 more rows
```

Check the main interaction

- Label: storyteller label (s: student; p: former prisoner)
- Condition: whether subject was assigned to intervention (i: intervention; c: control)
- Time: whether the survey was done before or after watching a film (1: before; 2: after)

```r
mapping <- c(
  "(Intercept)" = "Intercept",
  "visit.L" = "Time",
  "cond.L" = "Condition",
  "storyteller_label.L" = "Label",
  "cond.L:visit.L" = "Time*Condition",
  "cond.L:storyteller_label.L" = "Condition*Label",
  "storyteller_label.L:visit.L" = "Time*Label",
  "cond.L:storyteller_label.L:visit.L"="Time*Condition*Label"
)
```

```r
# Filter and map terms
selected_result <- rmse_fit_result |>
  filter(term %in% names(mapping)) |>
  mutate(term = recode(term, !!!mapping)) |>
  mutate(across(where(is.double), ~ round(., 3))) # easier to check
selected_result
```

```
# A tibble: 8 x 9
  effect term      estimate std.error statistic    df p.value conf.low conf.high
  <chr>  <chr>        <dbl>     <dbl>     <dbl> <dbl>   <dbl>    <dbl>     <dbl>
1 fixed  Intercept   27.6       1.02      27.0     580  0         25.6      29.7
2 fixed  Condition   -0.597     0.295     -2.03    580  0.043     -1.18     -0.018
3 fixed  Label       -0.338     0.164     -2.06   1797  0.039     -0.66     -0.017
4 fixed  Time        -0.515     0.164     -3.14   1797  0.002     -0.837    -0.194
5 fixed  Conditio~   -0.24      0.232     -1.03   1797  0.302     -0.695     0.215
6 fixed  Time*Con~   -0.595     0.232     -2.57   1797  0.01      -1.05     -0.14
7 fixed  Time*Lab~   -0.1       0.232     -0.433  1797  0.665     -0.555     0.355
8 fixed  Time*Con~   -0.674     0.328     -2.05   1797  0.04      -1.32     -0.03
```

However…Also the original study does not adjust their p-value…

Visualization

First compute how people emotion inference accuracy and compassion changed after watching the film

```r
# first compute how rating changes before and after watching a film
ea_change_table <- empathy_collapsed |>
  inner_join(subject_info |> select(obsID, movie), by="obsID") |>
  pivot_wider(
    names_from = visit,
    values_from = c(compassion, EArmse, EAcorr)
  ) |>
  mutate(
    compassion_diff = compassion_2 - compassion_1,
    corr_diff = EAcorr_2 - EAcorr_1,
    rmse_diff = EArmse_2 - EArmse_1
  ) |> mutate(
    acc_corr_diff = corr_diff,
    acc_rmse_diff = -rmse_diff
  ) |> mutate (
```

```
    cond = if_else(movie == "Just Mercy", "intervention", "control")
  ) |>
  select(
    obsID, cond, storyteller_label_attn_check,
    compassion_diff, acc_corr_diff, acc_rmse_diff)
```

T-test

A fast test of whether RMSE, correlation and compasion significantly increase or decrease, which is one of the important hypothesis to test.

```
test_increase_decrease <- function(data, col) {
  ttest <- t.test(data[[col]], mu=0);
  result <- tibble(
    mean = mean(data[[col]], na.rm = TRUE),
    t_stat = ttest$statistic,
    p_value = ttest$p.value,
    conf_low = ttest$conf.int[1],
    conf_high = ttest$conf.int[2]
  )
  result
}
```

- RMSE

```
# Test differences for each storyteller_label
rmse_ttests <- ea_change_table |>
  group_by(storyteller_label_attn_check, cond) |>
  summarise(
    test_results = list(test_increase_decrease(cur_data(), "acc_rmse_diff"))
  ) |>
  unnest(test_results) |>
  mutate(across(where(is.double), ~ round(., 3)))
rmse_ttests
```

```
# A tibble: 4 x 7
# Groups:   storyteller_label_attn_check [2]
  storyteller_label_attn_check cond       mean t_stat p_value conf_low conf_high
  <chr>                        <chr>     <dbl>  <dbl>   <dbl>    <dbl>     <dbl>
1 Formerly Incarcerated        control  -0.301  -0.73   0.466   -1.11      0.509
2 Formerly Incarcerated        interve~  1.81    4.17   0        0.957     2.66
```

```
3 Student                      control    0.506    1.12   0.265   -0.386     1.40
4 Student                      interve~   0.742    1.59   0.113   -0.177     1.66
```

The result suggests that emotion inference accuracy (measured by RMSE) change only significantly when story teller is labeled as 'Formerly Incarcerated' and the movie watched between the two surveys is the intervention one ('Just Mercy').

- CORR

```r
# Test differences for each storyteller_label
corr_ttests <- ea_change_table |>
  group_by(storyteller_label_attn_check, cond) |>
  summarise(
    test_results = list(test_increase_decrease(cur_data(), "acc_corr_diff"))
  ) |>
  unnest(test_results) |>
  mutate(across(where(is.double), ~ round(., 3)))

print(corr_ttests)
```

```
# A tibble: 4 x 7
# Groups:   storyteller_label_attn_check [2]
  storyteller_label_attn_check cond       mean t_stat p_value conf_low conf_high
  <chr>                        <chr>     <dbl>  <dbl>   <dbl>    <dbl>     <dbl>
1 Formerly Incarcerated        control  -0.023 -1.29    0.197   -0.058     0.012
2 Formerly Incarcerated        interve~  0.029  1.56    0.121   -0.008     0.066
3 Student                      control  -0.003 -0.162   0.871   -0.041     0.035
4 Student                      interve~  0.027  1.38    0.17    -0.012     0.066
```

Interestingly, the effect disappeared if instead pearson correlation is used to measure emotion inference accuracy

- Compassion

```r
# Test differences for each storyteller_label
compassion_ttests <- ea_change_table |>
  group_by(storyteller_label_attn_check, cond) |>
  summarise(
    test_results = list(test_increase_decrease(cur_data(), "compassion_diff"))
  ) |>
  unnest(test_results) |>
  mutate(across(where(is.double), ~ round(., 3)))
compassion_ttests
```

```
# A tibble: 4 x 7
# Groups:   storyteller_label_attn_check [2]
  storyteller_label_attn_check cond       mean t_stat p_value conf_low conf_high
  <chr>                        <chr>     <dbl>  <dbl>   <dbl>    <dbl>     <dbl>
1 Formerly Incarcerated        control   -4.36  -4.56   0        -6.24    -2.48
2 Formerly Incarcerated        interven~ -2.82  -2.76   0.006    -4.83    -0.813
3 Student                      control   -3.72  -4.03   0        -5.53    -1.90
4 Student                      interven~ -2.79  -2.34   0.02     -5.13    -0.442
```

Compassion overall decreases significantly in the second survey, regardless of number of the label of story-teller and the type of movies watched.

Finally, test whether there are group differences by two-sample ttest

```r
former_incarcerated <- ea_change_table |>
  filter(storyteller_label_attn_check == 'Formerly Incarcerated')

rmse_compare_ttest <- t.test(
  acc_rmse_diff ~ cond, data = former_incarcerated)
print(rmse_compare_ttest)
```

```
    Welch Two Sample t-test

data:  acc_rmse_diff by cond
t = -3.5284, df = 655.04, p-value = 0.0004473
alternative hypothesis: true difference in means between group control and group interventio
95 percent confidence interval:
 -3.2864196 -0.9363921
sample estimates:
     mean in group control mean in group intervention
                -0.3006644                  1.8107414
```

```r
compassion_compare_ttest <- t.test(
  compassion_diff ~ cond, data = former_incarcerated)
print(compassion_compare_ttest)
```

```
    Welch Two Sample t-test

data:  compassion_diff by cond
```

```
t = -1.1, df = 652.84, p-value = 0.2717
alternative hypothesis: true difference in means between group control and group interventio
95 percent confidence interval:
 -4.282368  1.207146
sample estimates:
     mean in group control mean in group intervention
                 -4.358310                  -2.820699
```

This suggests intervention only brings a significant difference for empathy but not compassion for former prisoner.

Replicate figure 1

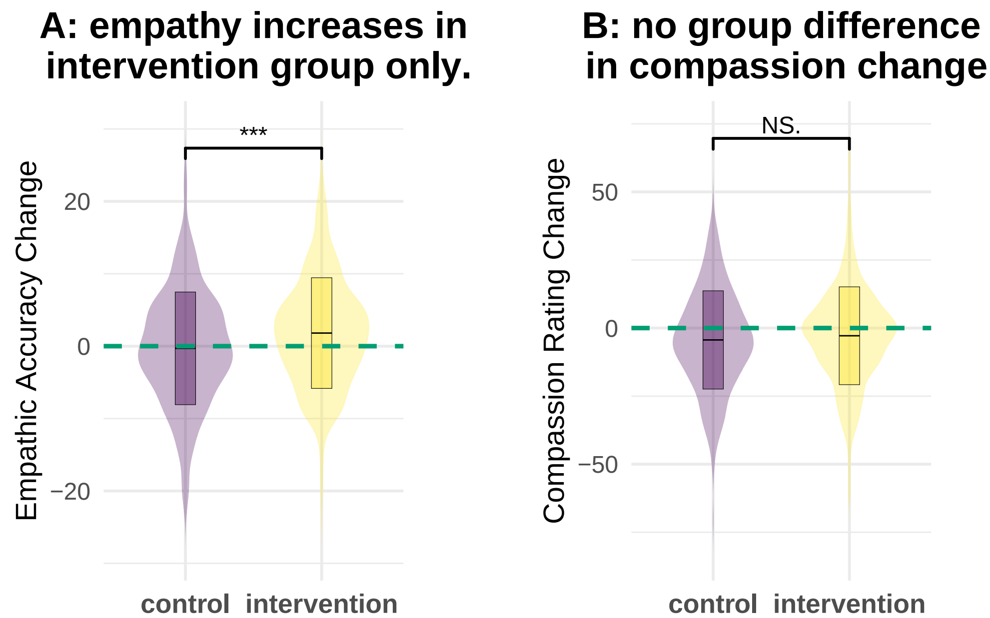
```r
library(ggplot2)
library(ggsignif)
library(gridExtra)
library(viridis)

pltA <- ggplot(
    former_incarcerated,
    aes(x = cond, y = acc_rmse_diff, fill = cond)) +
  geom_violin(
    trim = FALSE, alpha = 0.3, width=0.7, color=NA) +
  stat_summary(
    fun.data = mean_sdl, geom = "crossbar", fun.args=list(mult=1),
    width = 0.15, alpha=0.4, size=0.1) +
  geom_signif(
    comparisons = list(c("control", "intervention")),
    map_signif_level = TRUE, textsize=3) +
  geom_hline(
    yintercept = 0, linetype = "dashed", color="#009E73", size = 0.8) +
  labs(
    title = "A: empathy increases in\n intervention group only.",
    x = "", y = "Empathic Accuracy Change") +
  scale_fill_viridis_d(option="viridis") +
  theme_minimal() +
  theme(
    legend.position="none",
    aspect.ratio=1.6,
    plot.title=element_text(size=14, face = "bold", hjust = 0.5),
```

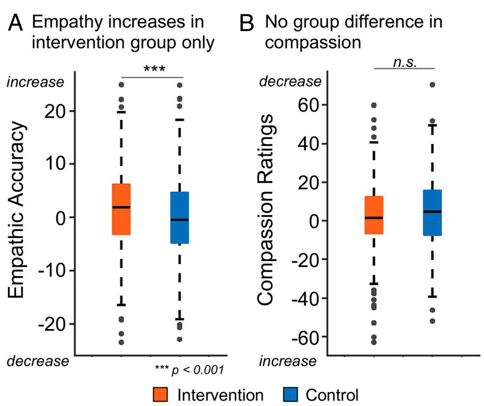
```r
    axis.text.x = element_text(size = 10, face = "bold")
  ) +
  theme(legend.position = "none")

pltB <- ggplot(
    former_incarcerated,
    aes(x = cond, y = compassion_diff, fill = cond)) +
  geom_violin(trim = FALSE, alpha = 0.3, width=0.7, color=NA) +
  stat_summary(
    fun.data = mean_sdl, geom = "crossbar",
    fun.args=list(mult=1), width = 0.15, alpha=0.4, size=0.1) +
  geom_signif(
    comparisons = list(c("control", "intervention")),
    map_signif_level = TRUE, textsize = 3) +
  geom_hline(
    yintercept = 0, linetype = "dashed", color="#009E73", size = 0.8) +
  labs(
    title = "B: no group difference\n in compassion change",
    x = "", y = "Compassion Rating Change") +
  scale_fill_viridis_d(option="viridis") +
  theme_minimal() +
  theme(
    legend.position="none",
    aspect.ratio=1.6,
    plot.title=element_text(size=14, face = "bold", hjust = 0.5),
    axis.text.x = element_text(size = 10, face = "bold")
  ) +
  theme(legend.position = "none")

grid.arrange(pltA, pltB, ncol = 2)
```



Compared to the original figure, the changes we've made include:



- Show the distribution.
- Use color-blindness friendly color palette.
- Fix the y label.
- Change the arrangement and size of different components.
- Flip the y axis for plot B.
- Stree the zero line.

References

- M.C. Reddan, S.B. Garcia, G. Golarai, J.L. Eberhardt, J. Zaki, Film intervention increases empathic understanding of formerly incarcerated people and support for criminal justice reform, Proc. Natl. Acad. Sci. U.S.A. 121 (44) e2322819121, https://doi.org/10.1073/pnas.2322819121 (2024).