A Comparative Analysis of Cooperation and Decision Times Between India and America

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Introduction

In the United States, a country of many cultures on the rampant path of globalization, the number of cross-cultural exchanges continually rises [Wu et al., 2009]. As a result, the demand for understanding and improving cross-cultural communication grows [Herrmann et. al, 2008]. Communication is the manner with which members of a society interact with one another, which in the past decades has been studied based on individual choices, particularly, cooperation and decision time [Rand and Nowak, 2013].Both of which take on different forms depending on the culture of their participants correlating with their respective social instiutions[Yamagashi 1988]. This is because social institutions enforce the social norms that shape the culture that influences how an individual communicates [Stagnaro et al., 2016].

However, despite the abundant research, different studies have produced contradictory results[Evans et al., 2015; Lohse et al., 2014]. Studies have shown all of the following: better cooperation with faster decision time, better cooperation with worse decision time, and the complete reverse for identical culture groups[Evans et al., 2015; Krajbich et al., 2015]. This is variance can be attributed to the varying degrees of conflictdness an individual experiences [Nishi et al., 2016].

In this study, we explore differences between United States and India as they vary in culture due to social institutions, and we allow for variations in conflictdness via participation in multiple rounds to see how both will impact cooperation and decision time [Buhrmester et al., 2011]. This procedure is possible through the use of powerful statistical tools that can handle large data sets, sort the data, and then perform statistical analyses and visualization. We expect individuals in the United States to make more cooperative decisions based on their social institutions ranking, however, due to the impact of individual conflictdness we can't guarantee this nor can we expect a certain difference in decision time relative to India. Due to the potential significance of these results, we emphasize the pipeline of statistical tools used. A brief overview of our pipeline includes collecting data from individuals in America and India in a Comma-Separated Values (CSV) file, performing commands in Python to sort the data, and finally utilizing Rstudio to analyze and visualize the data. As a result, we can outline the exact contribution specific factors have on cooperation and decision time.

Description/Methods

Country Selection

We selected India and the United States based on the Rule of Law Index 2015, which rates social institutions based on government constraints, corruption, open government, rights, order, and justice. On a 0-1 scale, United States was rated .73 and India was rated .51

[Henrich et al., 2010].

Recruitment

From each country, we recruited nearly 1200 participants from the Amazon Mechanical Turk online labor market where participants played in various games for 10 rounds totaling to 11340 decisions. For each decision, decision time and cooperation or defection was recorded. Following their first decision for each game, players had the choice to cooperate with or defect from other players that then formed their player environment. Players were only given information of how cooperative their overall player environment was prior to making this decision. No further information such as decision time was given. If the player cooperated with their player environment than the player environment would grow, and conversely defection would shrink the player environment. As a result each round, the player environment size would change.

Collected Data (Dataset)

All participant's from each country's location were traced based on the Internet Protocol(IP) address for a 24 hour ongoing study period. In a Comma Separated Values (CSV) file, we collected the following information for each player:

```
playerid,game,round,coop,prev_coop,prev_local_rate_coop,int_coop,
int_local_rate_coop,time,ltime,country_name

40100,1,10,0,0,0.111111111,1,0.888888889,2.602,0.415307292,United States
...
```

Data Key

Above for a player, we have the player id, the game number, the round number per game, coop(current cooperation/defection binary decision by player),prev_coop(last cooperation/defection binary decision by player), prev_local_rate_coop (last cooperation/defection rate of players environment),int_coop(initial binary cooperation/defection decision by player), int_local_rate_coop(cooperation/defection rate by 1st player environment),time (decision time), ltime(log(decision time)), and country_name(India or United States).

Sorting Data in Python

After retrieving the file, the data needed to be reformatted in Python so multiple rounds of information, such as coop or dec_time, could be attributed to a player.

Utilizing the following function we created a dictionary where for every player/player_id(key) we had a list of list (values for multiple rounds). The general format looks as following (key=[values for round 1],[values for round 2]...). Using following function we will produce 10 rounds of values for a player.

```python
# Working Function Below
#Open file, Read File, Remove Spaces
```

```
def completedic(filetext):
    with open(filetext, "r") as f:
        alldata = f.read().splitlines() [1:11]
# Create Dictionary with key=player and list of values=data
    res = {}
    for line in alldata:
        elements = line.split (",")
        player = elements[0]
        data = elements[1:]
# print(line) No error
# append new player by creating player and then add data,
#if player already there just add data
        if player not in res.keys():
            res[player] = []
            res[player].append(data)

        else:
            res[player].append(data)
#return appended dictionary
    return res
#remove keys with empty values in dictionary
aa = (completedic("/home/eeb177-student/Desktop/eeb-177
/eeb-174-final-project/formatted_CULT_data.csv"))
for player in list(aa.keys()):
    if player == '':
        del aa[player]
# print processed data
print (aa)
```

After which, the following functions extract a value at a given index for all lists for each key. They also remove unusual lines of data (less than 10 values, NA values, round 0, and countries not United States or India). For easier visualization in this paper, we extract only 1 player_id with their decision time info for all 10 rounds and write it to a new output file. However, all statistical analyses and data visualization are done with the full data set.

```python
#Created Output file, removed NA
def dec_time_round(aa):
    with open("1_dec_round.csv", "w") as f:
        f.write("player_id" + "," + "country" + "," +
        "round" + "," + "dec_time" +"\n")
        for key in aa.keys(): #key=player

            record = aa[key] #record=list of values for player,
```

```
            #len doesn't index at 0
#             print (key)
            if len(record) == 11:

                for ii in range(10): #range indexes at 0
                    country = record[1][9] # country shouldn't change
                    #across 10 records
                    rnd =  record[ii][1] # for every round, record
                    if country == "United States" or country == "India":
                    #selects for country
                        if (int(rnd) != 0): #selects for round 1-10
                                if (record[ii][2] != "NA"):
                                #removes lines with index 2 values of NA
                                    line=str(key) + "," + str(country) + "," +
                                    str(int(rnd)) + "," + str(record[ii][8])
                                    #pairs coop to round
                                    f.write(line + "\n")
#                                     print (line + "\n")


dec_time_round(aa)
```

player_id,country,round,dec_time 45717,United States,8,0.197004728 45717,United States,2,0.789792168 45717,United States,1,0.397244581 45717,United States,6,0.471144965 45717,United States,9,0.543198586 45717,United States,7,0.418467021 45717,United States,4,0.419955748 45717,United States,3,0.385069776 45717,United States,10,0.439016728

The output of function above and all those below were sent to separate output files:

player_id,country,round,prev_loc,dec_time(2_dec_time_prev_loc.csv)

player_id,country,round,prev_coop,dec_time (3_dec_time_prev_coop.csv)

player_id,country,round,coop (4_coop_time_round.csv)

player_id,country,round,prev_loc,coop (5_coop_prev_loc.csv)

player_id,country,round,prev_coop,coop(6_coop_prev_coop.csv)

country,round,coop(7_changing_coop.csv)

country,round,coop(8_changing_dec_time.csv)

All of functions can be found on the Github link at the end.

Statistical Analysis and Data Visualization in Rstudio

Using the respective output files and Rstudio,we created mixed effects models, performed data visualizations, and additional statistical tests to examine variance explained by fixed effects and random effects.

Mixed Effect Models: We downloaded the lme4 package to construct a linear mixed effects model that takes the form y~fixed effect(s) + random effect(s). We used this model to examine the fixed effects(country and round) on cooperation decision and decision time accounting for the following random effects (within player variance, variance of previous player environment, and variance of previous player decision).

We then utilized the newdata, data frame, to create a graph based on the predictive values of x rather than the fitted values.

Data Visualization and Statistical Tests: We downloaded ggplot2 to graph the mixed effects model with the newdata data frame. We graphed the fixed effects of country and round for cooperation decision and decision time with the random effect of within player variance. Ggplot in R produced a mixed effects model with information for each country and accounted for a 1 random effect. However, the graph it produced apart from showing a general trend was very difficult to read. We included this graph as outputs of mixed effects models are very rare for large data-sets as individual variation cannot be seen. However, for those using a much smaller data set this graphical output may be sufficient. Accounting for the poor visibility, we constructed additional graphs and completed Analysis of variance (ANOVA)'s to explore the effect of each fixed effect's on the response variable.

We included the additional graphs (using only fixed effects) for theaverage decision time and cooperation between each country, so a reader could see the general trend. We did not however show statistics as they would be without consideration of random effects. To create these graphs, we first created a data frame of the average cooperation and decision times for each country for each round. We then installed a new package Rmisc to summarize the data and calculate the standard error. Next we used ggplot2 to produce a graphical output comparing the averages for each country for each round.

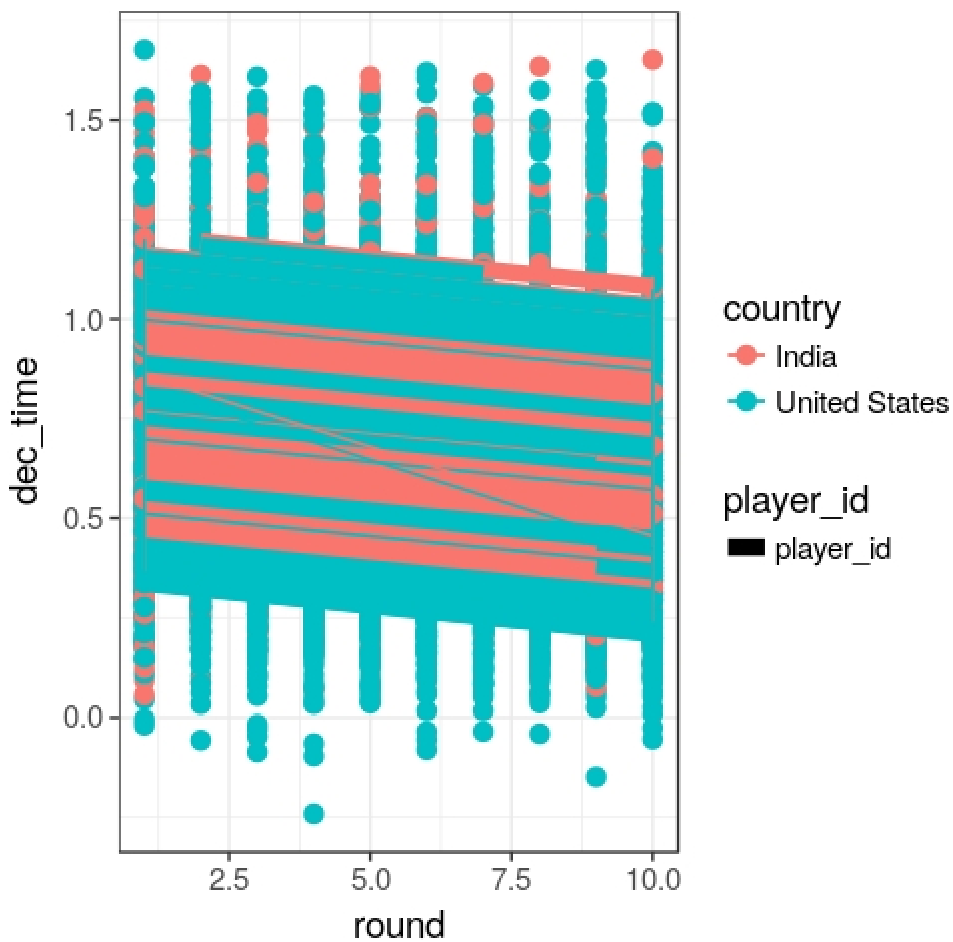
Results For our first mixed effects linear model we examined the effects of player_id, country, and round on decision time.

```
library(ggplot2)
library(lme4)
Data <-read.csv("/home/eeb177-student/Desktop/eeb-177/eeb-174-final-project
                /1_dec_round.csv")
reg1 <- lmer(dec_time ~ country  + round + (1|player_id), data=Data,
             REML=FALSE)
#summary(reg1)

#predict y value by x
newdat <- expand.grid(country=unique(Data$country), player_id =
                        unique(Data$player_id),
                  round=c(min(Data$round),
                      max(Data$round)))
#graph prediction
library(ggplot2)
p <- ggplot(Data, aes(x=round, y=dec_time, colour=country)) +
```

```r
  geom_point(size=3) +
  geom_line(aes(y=predict(reg1), group=player_id, size="player_id"))
+ geom_line(data=newdat, aes(y=predict(reg1, newdata=newdat))) +
  scale_size_manual(name="player_id", values=c("player_id"=3,
  "country"=3)) +
  theme_bw(base_size=14)
print(p)
```

Decision Time for a player in India and United States

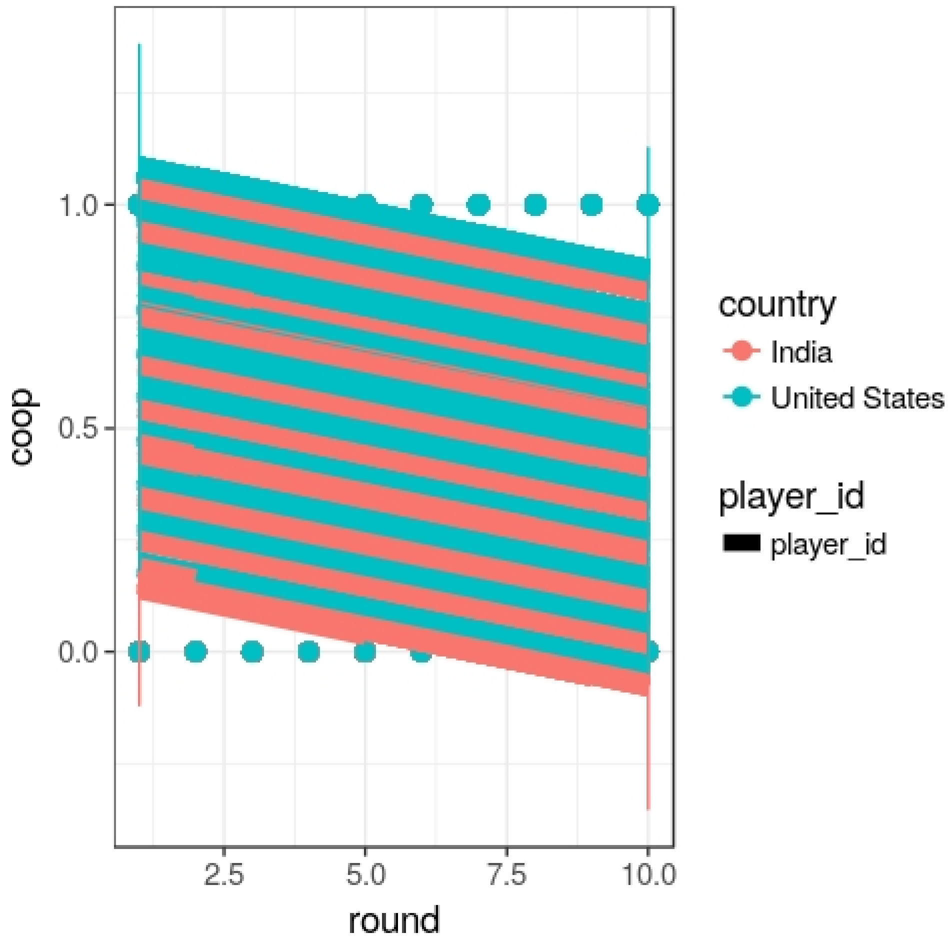


Accounting for player variation, country affected decision time (Chi-Square(1)=, 1782.1, p=.0065).The United States had a lower decision time by 0.0328552 seconds +/- 0.0120496 Standard Error (figure 1). Accounting for player variation, round affected decision time (Chi-Square(1)=, 1782.1, p<2.2e-16).The United States had a lower decision time by 0.0140937 seconds +/- 0.0007868 Standard Error(figure 1).

```
#country
reg4 <- lmer(dec_time ~ round + (1|player_id), data=Data,REML=FALSE)
reg5 <- lmer(dec_time ~ country + round + (1|player_id), data=Data,REML=FALSE)
anova(reg4,reg5)
#round
reg2 <- lmer(dec_time ~ country + (1|player_id), data=Data,REML=FALSE)
reg3 <- lmer(dec_time ~ country + round + (1|player_id), data=Data,REML=FALSE)
anova(reg2,reg3)
```

For our second linear mixed effects model we examined the effects of player_id, country, and round on cooperation.

Cooperation for a player in India and United States



Accounting for player variation, country affected cooperation (Chi-Square(1)=, 172, p<2.2e-16).The United States had a higher cooperation by 0.302786 +/- 0.022311 Standard Error (figure 2). Accounting for player variation, round affected cooperation (Chi-Square(1)=, 507.61, p<2.2e-16). The United States had a lower cooperation by 0.025684 +/- 0.001126 Standard Error (figure 2).

```
#country
reg4 <- lmer(coop ~ round + (1|player_id), data=Data,REML=FALSE)
reg5 <- lmer(coop ~ country + round + (1|player_id), data=Data,REML=FALSE)
anova(reg4,reg5)
#round
reg2 <- lmer(coop ~ country + (1|player_id), data=Data,REML=FALSE)
reg3 <- lmer(coop ~ country + round + (1|player_id), data=Data,REML=FALSE)
anova(reg2,reg3)
```

However, accounting for the random effect of variance of previous player environment, and variance of previous player decision our effects of country and round on cooperation and decision time changed.

Accounting for player variation and variance of previous player decision, country affected decision time (s) (Chi-Square(1)=, 1618.5, p=.006942).The United States had a lower decision time by .0334826 +/- 0.0123772 Standard Error. Accounting for player variation, round affected cooperation (Chi-Square(1)=, 1613.2, p<2.2e-16).The United States had a lower decision time by 0.0111741 +/- 0.0009384 Standard Error.

```
reg4 <- lmer(dec_time ~ round + (1|player_id) + (1|prev_loc),
             data=Data, REML=FALSE)
reg5 <- lmer(dec_time ~ country  + round + (1|player_id) + (1|prev_loc),
             data=Data, REML=FALSE)
anova(reg4,reg5)
#round
reg2 <- lmer(dec_time ~ country + (1|player_id) + (1|prev_loc),
             data=Data,             REML=FALSE)
reg3 <- lmer(dec_time ~ country  + round + (1|player_id) + (1|prev_loc),
             data=Data, REML=FALSE)
anova(reg2,reg3)
(summary 1)
```

Accounting for player variation and variance of previous player player environment, country affected decision time (s) (Chi-Square(1)=, 1618.5, p=.006942). The United States had a lower cooperation by 0.0356957 +/- 0.0123590 Standard Error. Accounting for player variation, round affected cooperation (Chi-Square(1)=, 1618.5, p<2.2e-16). The United States had a lower cooperation by 0.0110372 +/- 0.0009202 Standard Error.

```
#country
reg4 <- lmer(coop ~ round + (1|player_id) + (1|prev_loc),
             data=Data, REML=FALSE)
```

```
reg5 <- lmer(coop ~ country  + round + (1|player_id) + (1|prev_loc),
             data=Data, REML=FALSE)
anova(reg4,reg5)
#round
reg2 <- lmer(coop ~ country  + (1|player_id) + (1|prev_loc),
             data=Data, REML=FALSE)
reg3 <- lmer(coop ~ country  + round + (1|player_id) + (1|prev_loc),
             data=Data, REML=FALSE)
anova(reg2,reg3)
(summary 2)
```

Accounting for player variation and variance of previous player decision, country affected cooperation (Chi-Square(1)=, 9180.5, p< 2.2e-16). The United States had a higher cooperation by 0.265919 +/- 0.020898 Standard Error. Accounting for player variation and variance of previous player decision, round affected cooperation (Chi-Square(1)=, 9180.5, p<2.2e-16). The United States had a lower cooperation by-0.026175 +/- 0.001324 Standard Error.

```
#country
reg4 <- lmer(coop ~ round + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
reg5 <- lmer(coop ~ country  + round + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
anova(reg4,reg5)
#round
reg2 <- lmer(coop ~ country  + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
reg3 <- lmer(coop ~ country  + round + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
anova(reg2,reg3)
(summary 3)
```

Accounting for player variation and variance of previous player player decision, country affected decision time (Chi-Square(1)=, 1631.2, p=.003931).The United States had a lower decision time by 0.0356957 +/- 0.0123590 Standard Error. Accounting for player variation, round affected cooperation (Chi-Square(1)=, 1631.2, p<2.2e-16). The United States had a lower decision time by 0.0110372 +/- 0.0009202 Standard Error.

```
#country
reg4 <- lmer(dec_time ~ round + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
reg5 <- lmer(dec_time ~ country  + round + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
anova(reg4,reg5)
#round
reg2 <- lmer(dec_time ~ country  + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
```

```
reg3 <- lmer(dec_time ~ country  + round + (1|player_id) + (1|prev_coop),
             data=Data, REML=FALSE)
anova(reg2,reg3)
(summary 4)
```

As previously mentioned in our methods, this is our a simpler graph used for understanding the average decision time between each country as the mixed effect data visualization in R is poor.

Cooperation for a player in India and United States

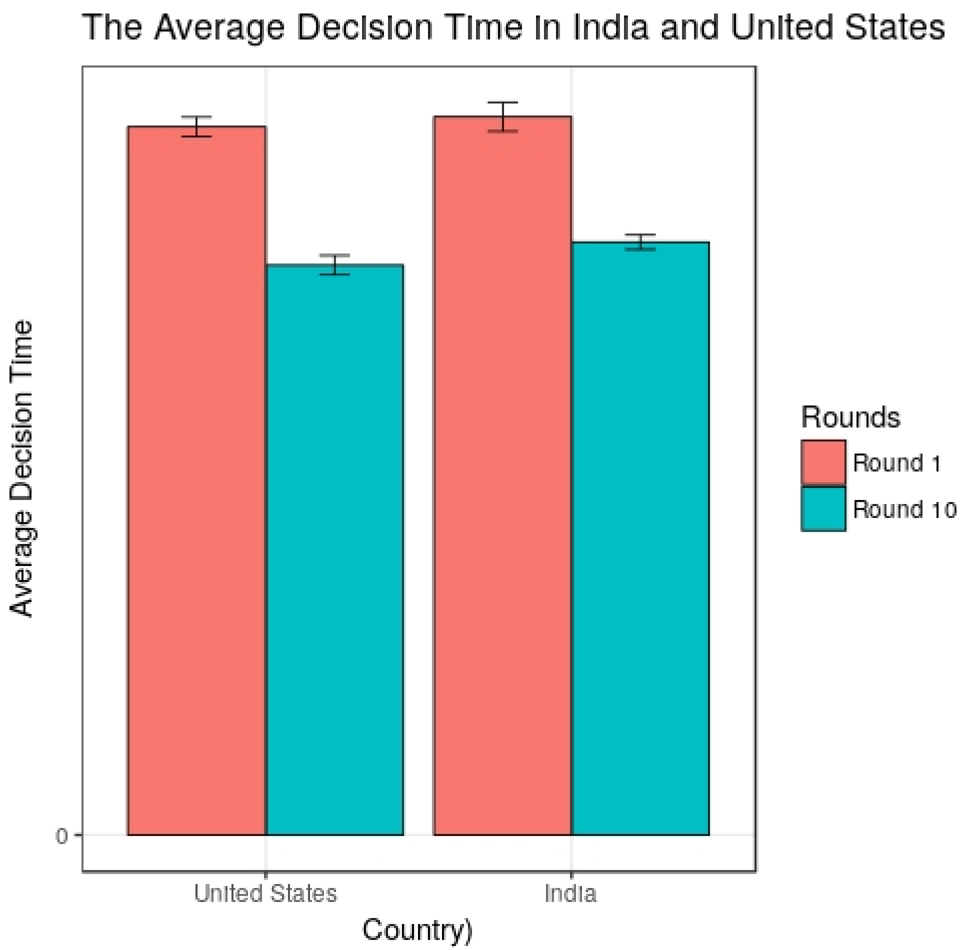


Figure 1: figure 3

This is our graphical for average cooperation between each country.

Cooperation for a player in India and United States

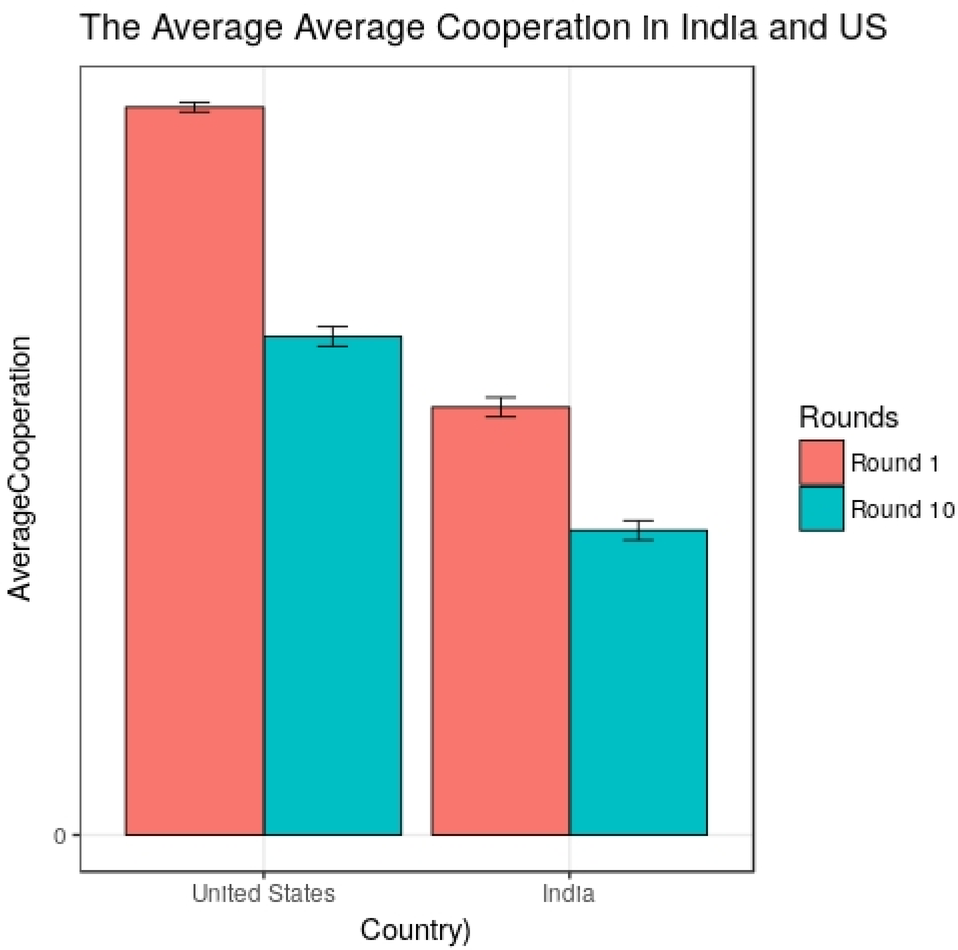


Figure 2: figure 4

Discussion

Through our research, we found significant differences between United States and Indian subjects in terms cooperation and decision time. We were able to examine the effects of conflictdness through examining decision times for multiple rounds as well as the effects of culture by examining players in the United States and India. We saw in the simplified models that initially, with no knowledge of their player environment, players from the United States were more likely to be initially cooperative, but slowly became less cooperative as the rounds went on (figure 3)(figure4).

Comparing the two countries, via the mixed effects model, we found that for all cases the contribution of country outweighed that of round for either cooperation or decision time (figure 1) (figure 2)(summary 1)(summary 2)(summary 3)(summary 4). We found that cooperation increased in the United States,relative to India, when player variance and variance in previous player decisions were included (summary 2). However, cooperation decreased slightly when only including variance of the player environment (summary 3). This supports the evidence that a sub-culture may have a greater affect on our cooperation than national culture. As a result of the opposing effects, random effects bear significant effects for modeling cooperation. On the other hand, United States had significantly lower decisions for any combination of random effects as a result players overall experience less conflicted-ness (figure1)(summary1)(summary4).

Through this study, we demonstrate the significant differences cross-cultural differences in human cooperation due to a statistical pipeline that we used. Based on examining cooperation and decision via a fixed effects graphical model and a mixed-effects model, we noted the significant benefit with examining a fixed effects model. Additionally, we learned that the random effects of within player variance, variance of previous player environment, and variance of previous player decision had varying effects on decision and cooperation. As a result, future studies should utilize a mixed effects model for statistical analysis.

GitHub link: https://github.com/ashenparikh/eeb-174-final-project/blob/master/Culture_Cooperation_DecisionTime_FinalProject.pdf

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