Physical Pragmatics (decider_2)

Preprocessing

```
# Read in the participant data.
data_0 = read_csv(file.path(data_path, "raw_data.csv"), quote="~")

# Convert the JSON string into JSON.
data_1 = lapply(data_0$data, fromJSON)

# Extract the trial information for each participant and stack them.
data_3 = tibble()
for (p in 1:length(data_1)) {
  # Trim the map and add the participant ID back in.
  data_2 = data_1[p][[1]]$trials %>%
    as.data.frame() %>%
    separate(stimuli, into=c("door", "cost", "object"), sep="_") %>%
    mutate(object=gsub(".png", "", object),
           target=as.numeric(target),
           unique_id=data_1[p][[1]]$id,
           age=as.numeric(data_1[p][[1]]$subject_information$age))

  # Stack the trial information for the current participant.
  data_3 = rbind(data_3, data_2)
}

# Write the preprocessed data.
write_csv(data_3, file.path(data_path, "data.csv"))
```

"Unusualness" as a predictor of communicative association

First, we analyze the predictive power of participant "unusualness" judgments (N=80, M=34.04 years, SD=15.1 years) on the participant judgments from `decider_1`.

```
# Read in the preprocessed participant data.
data_3 = read_csv(file.path(data_path, "data.csv"))

# Compute the mean participant judgments.
data_4 = data_3 %>%
  select(cost, object, target) %>%
  group_by(cost, object) %>%
  summarize(unusualness=mean(target))

# Read in the preprocessed participant data from Experiment 1.
```

```r
data_5 = read_csv("data/decider_1/data_0/data.csv") %>%
  rbind(read_csv("data/decider_1/data_1/data.csv")) %>%
  rbind(read_csv("data/decider_1/data_2/data.csv"))

# Filter the trial and columns of interest and append the "unusualness"
# judgments.
data_6 = data_5 %>%
  rename(response=target) %>%
  filter(trial=="trial_1") %>%
  select(response, object) %>%
  mutate(cost=ifelse(response==0, "none", "low")) %>%
  left_join(data_4)

# Compute a logistic regression predicting `decider_1` participant judgments as
# a function of "unusualness" judgments.
model_0 = glm(response~unusualness, data=data_6, family="binomial")
summary(model_0)
```

```
##
## Call:
## glm(formula = response ~ unusualness, family = "binomial", data = data_6)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3197  -0.6736   0.3652   0.7837   1.1017
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   -2.934      1.004  -2.921 0.003484 **
## unusualness    7.946      2.116   3.756 0.000173 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 81.854  on 69  degrees of freedom
## Residual deviance: 59.046  on 68  degrees of freedom
##   (10 observations deleted due to missingness)
## AIC: 63.046
##
## Number of Fisher Scoring iterations: 5
```

"Unusualness" as a predictor of communicative meaning

Now, we analyze the predictive power of participant "unusualness" judgments (N=80, M=34.04 years, SD=15.1 years) on the participant judgments from `decider_0`. This time, we'll also include the cost condition as a predictor. If both predictors are significant, we will run a second analysis to determine whether or not the cost condition can explain the unexplained variance from participant "unusualness" judgments.

```r
# Read in the preprocessed data for the first partition.
data_7 = read_csv("data/decider_0/data_0/data.csv") %>%
  rbind(read_csv("data/decider_0/data_1/data.csv"))

# Exclude participants who said the unmodified door was more difficult to walk
# through and chop off the extra participant in the low-cost condition.
data_8 = data_7 %>%
  filter(costlier!="unmodified", participant!=161)

# Filter the columns of interest and append the unusualness judgments.
data_9 = data_8 %>%
  rename(cost=condition) %>%
  select(response, cost, object) %>%
  full_join(data_4)

# Compute a logistic regression predicting `decider_0` participant judgments as
# a function of participant "unusualness" judgments and the cost condition.
model_1 = glm(response~unusualness+cost, data=data_9, family="binomial")
summary(model_1)
```

```
##
## Call:
## glm(formula = response ~ unusualness + cost, family = "binomial",
##     data = data_9)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.3900  -1.0398   0.4870   0.7676   1.3216
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.4403     0.7027   0.627   0.5309
## unusualness   2.3756     1.0176   2.334   0.0196 *
## costnone     -0.9702     0.4707  -2.061   0.0393 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 184.21  on 159  degrees of freedom
## Residual deviance: 162.16  on 157  degrees of freedom
## AIC: 168.16
##
## Number of Fisher Scoring iterations: 4
```

Both predictors are significant, so we will run a series of regressions to test whether or not the cost condition can explain any of the unexplained variance left by "unusualness".

```r
# Compute a logistic regression predicting `decider_0` participant judgments as
# a function of participant "unusualness" judgments.
model_2 = glm(response~unusualness, data=data_9, family="binomial")

# Extract the residuals (i.e., unexplained variance) from the previous model.
```

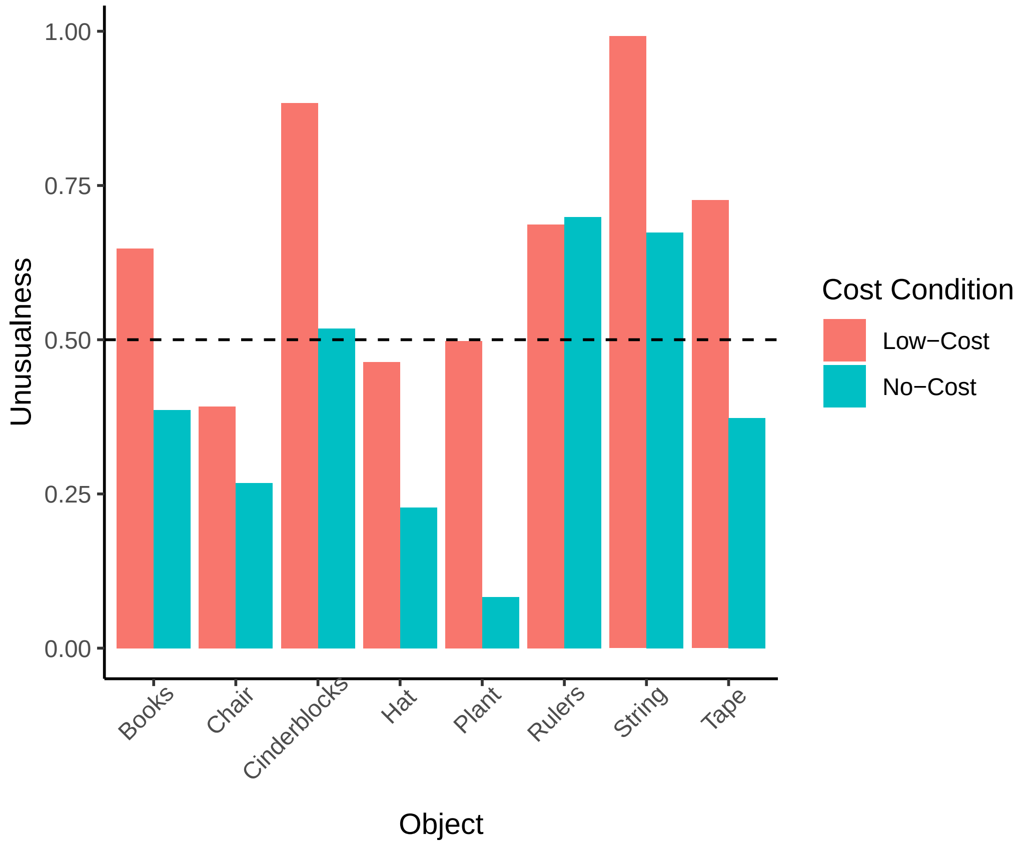
```
data_9$residuals = resid(model_2)

# Compute a linear regression predicting the residuals as a function of the
# cost condition.
model_3 = glm(residuals~cost, data=data_9, family="gaussian")
summary(model_3)
```

```
##
## Call:
## glm(formula = residuals ~ cost, family = "gaussian", data = data_9)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -2.6899  -0.9682   0.2654   0.6394   1.3953
##
## Coefficients:
##             Estimate Std. Error t value Pr(>|t|)
## (Intercept)   0.3110     0.1120   2.776  0.00616 **
## costnone     -0.3619     0.1584  -2.284  0.02368 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for gaussian family taken to be 1.003894)
##
##     Null deviance: 163.85  on 159  degrees of freedom
## Residual deviance: 158.62  on 158  degrees of freedom
## AIC: 458.67
##
## Number of Fisher Scoring iterations: 2
```

Comparing “unusualness” judgments by cost condition

```
plot_0 = data_4 %>%
  ggplot(aes(x=object, y=unusualness, fill=cost)) +
  geom_bar(stat="identity", position=position_dodge()) +
  geom_hline(yintercept=0.5, linetype="dashed") +
  theme_classic() +
  theme(aspect.ratio=1.0,
        axis.text.x=element_text(angle=45, hjust=0.8)) +
  scale_x_discrete(name="Object",
                   limits=c("books", "chair", "cinderblocks", "hat", "plant",
                            "rulers", "string", "tape"),
                   labels=c("Books", "Chair", "Cinderblocks", "Hat", "Plant",
                            "Rulers", "String", "Tape")) +
  ylab("Unusualness") +
  scale_fill_discrete(name="Cost Condition",
                      limits=c("low", "none"),
                      labels=c("Low-Cost", "No-Cost"))
plot_0
```


Unusualness
1.00
0.75
0.50
0.25
0.00
Books
Chair
Cinderblocks
Hat
Plant
Rulers
String
Tape
Object
Cost Condition
Low−Cost
No−Cost