PSYC575 Course Project

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Load packages

```
library(tidyverse)
library(psych)
library(lme4)
library(broom.mixed)
library(brms)
library(modelsummary)
library(haven)  # for importing SPSS/SAS/Stata data
library(lmerTest)  # for testing coefficients
library(MuMIn)  # for R^2
library(lattice)  # for dotplot (working with lme4)
library(ggplot2)
library(sjPlot)  # for plotting effects
# Add the following so that the LOO will be included in the msummary table
glance_custom.brmsfit <- function(x) {
  broom.mixed::glance(x, looic = TRUE)
}
theme_set(theme_bw())  # Theme; just my personal preference
```

Import Data

```
setwd("/Users/qianhuini/Desktop/USC/Study/2020 Fall/575_Multilevel Modeling/575_project")
ToM_dat <- read.csv("ELdataset.csv")
head(ToM_dat)
```

```
##   Subject RT_ID_AD_p RT_ID_AU_p RT_ID_AD_a RT_ID_AU_a RT_LO_AD_p RT_LO_AU_p
## 1       1       1208       1197       2105        933       1554       3255
## 2       1       1017       1160       1063       1541       1192       1265
## 3       1       1050       1243       1076       1236       1044       1324
## 4       1        914       1024       1159        904       1319       1454
## 5       1        924       1133        821        890       1586       1328
## 6       1       1539       1615       1096       1492       1073       1677
##   RT_LO_AD_a RT_LO_AU_a ERR_ID_AD_p ERR_ID_AU_p ERR_ID_AD_a ERR_ID_AU_a
## 1       1909       1389           1           1           1           1
## 2       2205       1810           1           1           1           1
## 3       1134       1240           1           1           1           1
## 4       3375        979           1           1           1           1
## 5       1076        996           1           1           1           1
## 6       1366       1044           1           1           1           0
##   ERR_LO_AD_p ERR_LO_AU_p ERR_LO_AD_a ERR_LO_AU_a
## 1           0           1           1           1
```

```
## 2              1              1              1              1
## 3              1              1              1              1
## 4              1              1              1              1
## 5              1              1              1              1
## 6              1              1              1              1
```

For data storage needs, the name of each column is slightly modified. The "+" and "-" in the original dataset are changed to "p" for presence and "a ' for absence.

Data Preprocessing

The original dataset is in wide-format and with `rt` and `err` together, so I break it into two subsets and then transform them to long-format. Log transformation is also performed for the variable `rt`. There are two predictions: `Task` and `Condition`, so I will separate them too during the transformation.

```r
# Seperate into two subsets
ToM_rt_wide <- ToM_dat[,1:9]
ToM_err_wide <- ToM_dat[,c(1,10:17)]
# Covert to long-format dataset
ToM_rt <- ToM_rt_wide %>%
  pivot_longer(
    cols = RT_ID_AD_p:RT_LO_AU_a,
    names_to = "Condition",
    names_prefix = "rt",
    values_to = "rt",)
ToM_rt$Task <- substring(ToM_rt$Condition, 4,5)
ToM_rt$Condition <- sub('^......','',ToM_rt$Condition)

ToM_err <- ToM_err_wide %>%
  pivot_longer(
    cols = ERR_ID_AD_p:ERR_LO_AU_a,
    names_to = "Condition",
    names_prefix = "err",
    values_to = "err",)
ToM_err$Task <- substring(ToM_err$Condition, 5,6)
ToM_err$Condition <- sub('^.......','',ToM_err$Condition)

# Log transformation for rt
ToM_rt$lg_rt <- log(ToM_rt$rt)
ToM_rt <- ToM_rt[,c(1,4,2,3,5)]
head(ToM_rt)
```

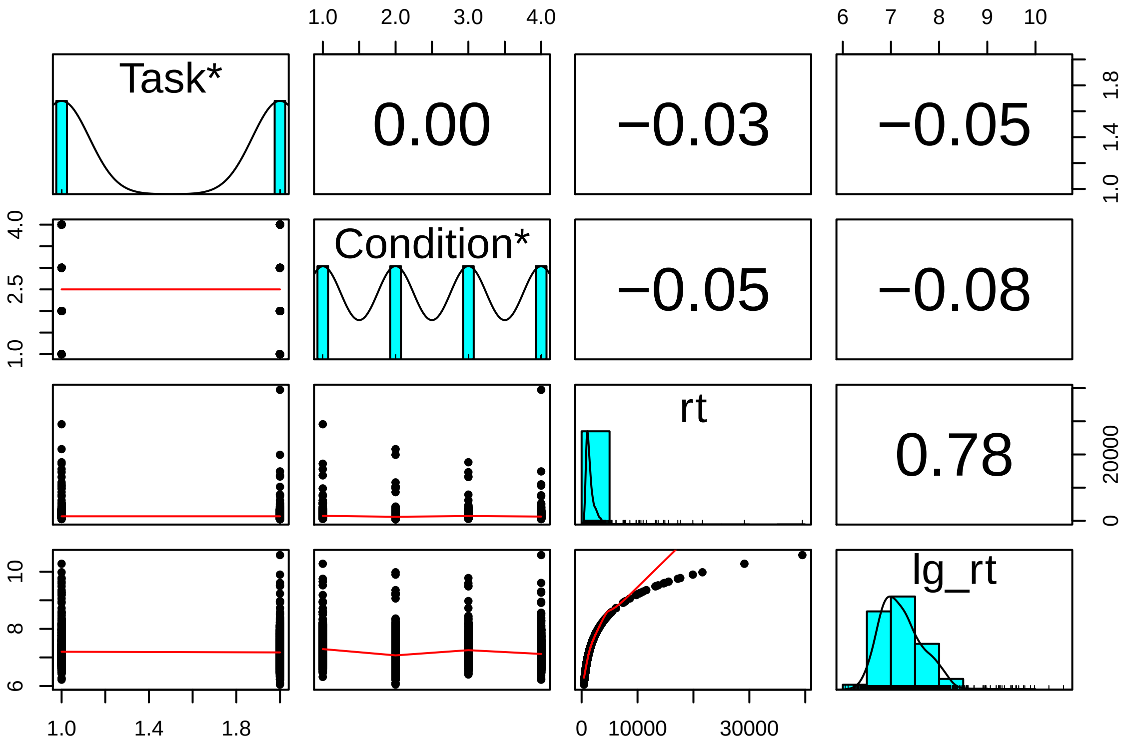
```
## # A tibble: 6 x 5
##   Subject Task  Condition    rt lg_rt
##     <int> <chr> <chr>     <int> <dbl>
## 1       1 ID    AD_p       1208  7.10
## 2       1 ID    AU_p       1197  7.09
## 3       1 ID    AD_a       2105  7.65
## 4       1 ID    AU_a        933  6.84
## 5       1 LO    AD_p       1554  7.35
## 6       1 LO    AU_p       3255  8.09
```

Analysis of Reaction Time

There are two outcome variables: `rt` and `err`. They will be analyzed separately.

1. Data Exploration

```
pairs.panels(ToM_rt[ , -1],
             ellipses = FALSE)
```



2. Unconditional model with random intercepts

I first run an unconditional model with random intercepts of both `Subject` and `Task`. The major research question is the effect of `Task` on `rt`, so here I will include `Task` and `Subject`.

Repeated measure (within-cell) level (lv1):

$$\lg \text{rt}_{i(j,k)} = \beta_{0(j,k)} + e_{ijk}$$

Between-cell (Subject x Task) level:

$$\beta_{0(j,k)} = \gamma_{00} + v_{0k}$$

```
m0_rt <- lmer(lg_rt ~ (1 | Subject) + (1 | Task), data = ToM_rt)
vc_m0_rt <- as.data.frame(VarCorr(m0_rt))

# Proportion of variance at the within-cell level
icc_e_rt <- vc_m0_rt$vcov[3] / sum(vc_m0_rt$vcov)

# ICC/Deff (Subject; cluster size = 2)
icc_subj_rt <- vc_m0_rt$vcov[1] / sum(vc_m0_rt$vcov)
c("ICC(subj_rt)" = icc_subj_rt,
  "Deff(subj_rt)" = 1 + (2 * icc_subj_rt))
```

```
##  ICC(subj_rt) Deff(subj_rt)
##     0.2347063     1.4694125
```

```r
# ICC/Deff (Task; cluster size = 40)
icc_task_rt <- vc_m0_rt$vcov[2] / sum(vc_m0_rt$vcov)
c("ICC(Task_rt)" = icc_task_rt, "Deff(Task_rt)" = icc_e_rt + 40 * icc_task_rt)
```

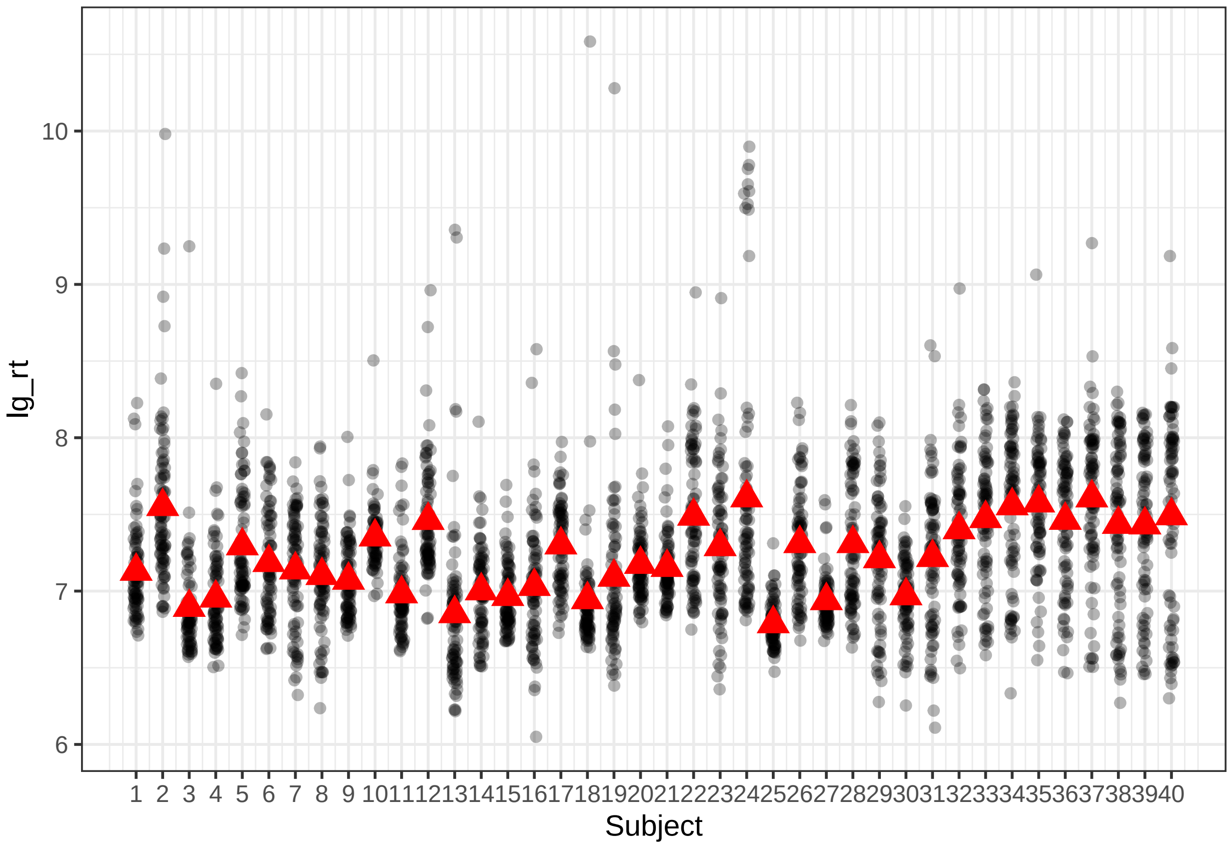
```
##  ICC(Task_rt) Deff(Task_rt)
##    0.00440324    0.93702010
```

```r
c("ICC(Subject_rt + Task_rt)" = sum(vc_m0_rt$vcov[1:2]) / sum(vc_m0_rt$vcov))
```

```
## ICC(Subject_rt + Task_rt)
##                 0.2391095
```

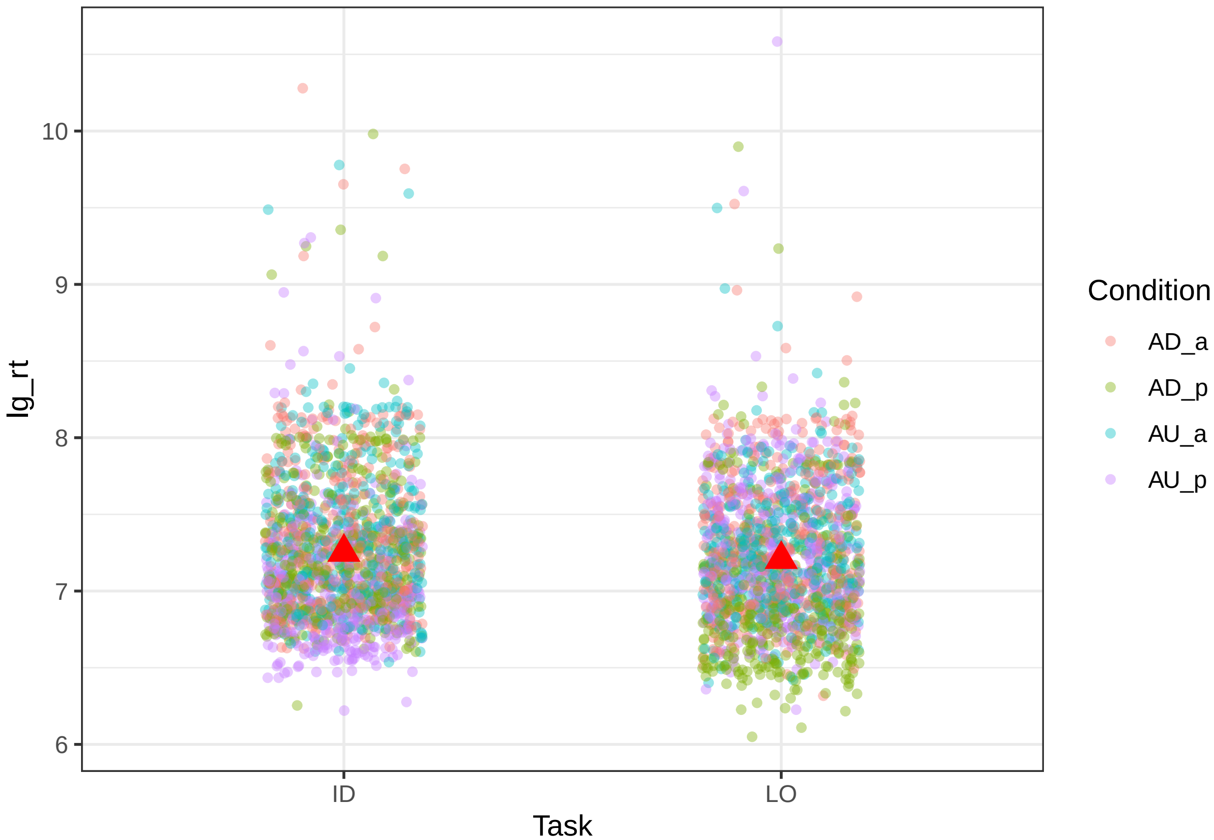
The results show that the ICC of `Subject` is .235 with the design effect of 1.469. This means that we can expect a week correlation between two randomly drawn units from the same subject. This is quite reasonable because the same person will have a certain reaction pattern and a range of reaction times. Next, the ICC of `Task` is .004 with the design effect of .937. Together, the ICC is .239.
The variations across persons, acorss tasks, and across conditions are plotted as below.

```r
# Variation across persons
sub_ids <- unique(ToM_rt$Subject)
(p_set <- ToM_rt %>%
    filter(Subject %in% sub_ids) %>%
    ggplot(aes(x = Subject, y = lg_rt)) +
    geom_jitter(height = 0, width = 0.1, alpha = 0.3) +
    scale_x_continuous(breaks = sub_ids, labels = sub_ids) +
    # Add subject means
    stat_summary(
      fun = "mean",
      geom = "point",
      col = "red",
      shape = 17,
      # use triangles
      size = 4)
)
```

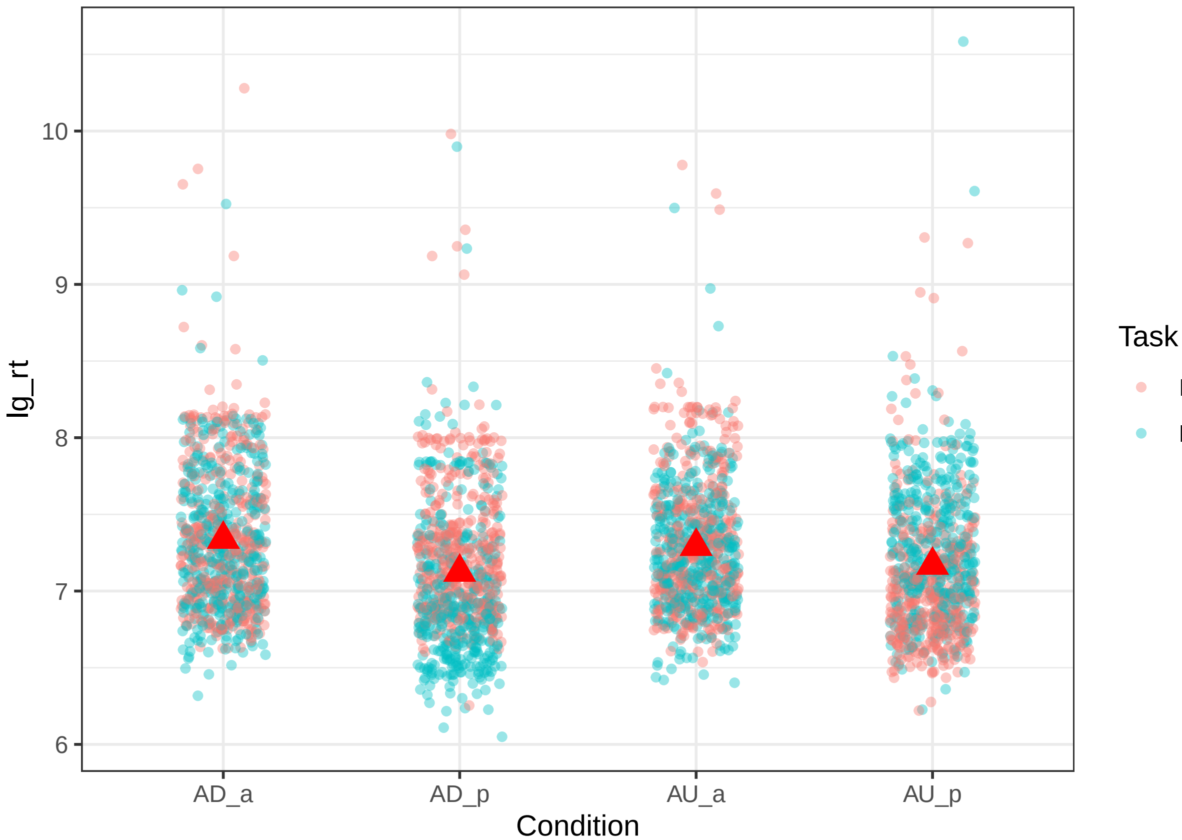



```
par(mfrow=c(1,2))

# Variation across tasks
task_ids <- unique(ToM_rt$Task)
ggplot(aes(x = Task, y = lg_rt, color=Condition),data = ToM_rt) +
  geom_jitter(height = 0, width = 0.18, alpha = 0.4, size = 1.2) +
  stat_summary(
    fun = "mean",
    geom = "point",
    col = "red",
    shape = 17,
    size = 4)
```




```r
# Variation across conditions
condition_ids <- unique(ToM_rt$Condition)
ggplot(aes(x = Condition, y = lg_rt, color=Task),data = ToM_rt) +
  geom_jitter(height = 0, width = 0.18, alpha = 0.4, size = 1.2) +
  stat_summary(
    fun = "mean",
    geom = "point",
    col = "red",
    shape = 17,
    size = 4)
```




```
par(mfrow=c(1,1))
```

3. Judgement

The major experimental manipulation is task, which has two values: ID if it is in the Identity Task, and LO if the it is in the Location Task.
Because the hypothesis is phrased such that Location task is easier to process, we'll make Identity task the reference group by making the variable a factor with Identity task as the first category.

```
ToM_rt <- ToM_rt %>%
  mutate(Task = factor(Task, levels = c("ID", "LO")))
```

4. Modeling for `rt`

4.1 Model Equations

Repeated-Measure level (Lv 1):

$$\lg \text{rt}_{i(j,k)} = \beta_{0(j,k)} + e_{ijk}$$

Lv 2:

$$\beta_{0(j,k)} = \gamma_{00} + \beta_{1j}\text{Task}_{ik} + \beta_{2j}\text{Condition}_{ik} + \beta_{3j}\text{Task}_{ik} \times \text{Condition}_{ik} + u_{0j} + v_{0k}$$

Condition level (Lv 2a) random slopes

$$\beta_{1j} = \gamma_{10} + +u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + u_{3j}$$

Combined equations

$$
\begin{aligned}
\lg \mathrm{rt}_{i(j,k)} = {} & \gamma_{00} \\
& + \gamma_{10}\mathrm{Task}_{ik} + \gamma_{20}\mathrm{Condition}_{ik} + \gamma_{30}\mathrm{Condition}_{ik} \times \mathrm{Task}_{ik} + \\
& + u_{0j} + u_{1j}\mathrm{Task}_{ik} + u_{2j}\mathrm{Condition}_{ik} + u_{3j}\mathrm{Task}_{ik} \times \mathrm{Condition}_{ik} \\
& + v_{0k} + e_{ijk}
\end{aligned}
$$

4.2 Fit a Model

Here I fit a Bayesian multilevel model to estimate the effect of `Task` on ‘`rt`. The multilevel models were fitted using the brms package (Bürkner, 2017) in R, which performs Markdov Chain Monte Carlo approximation with the No U-Turn Sampler to approximate the posterior distributions of the model parameters. For each model, 4 chains are used, each with 2,000 iterations (1,000 warmup). The default priors from brms were used, which include uniform non-informative priors on the fixed-effect parameters and weakly informative Student-t priors on the standard deviations of the random effects. For all model, Rhat < 1.01 (Vehtari et al., 2020), indicating convergence of the chains to a stationary posterior distributions. The posterior distributions of the model parameters are summarized using the posterior means and the 95% equal-tailed credible intervals.

```
m1_rt <- brm(lg_rt ~ Task + (Task | Subject) + (Task | Condition),
             data = ToM_rt,
             control = list(adapt_delta = .9),
             cores = 2)
```

```
## Compiling Stan program...
```

```
## Trying to compile a simple C file
```

```
## Running /Library/Frameworks/R.framework/Resources/bin/R CMD SHLIB foo.c
## clang -mmacosx-version-min=10.13 -I"/Library/Frameworks/R.framework/Resources/include" -DNDEBUG   -I
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/StanHeaders/incl
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/inclu
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/inclu
## /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/include/Eigen/src/Core/util/
## namespace Eigen {
## ^
## /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/include/Eigen/src/Core/util/
## namespace Eigen {
##                ^
##                ;
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/StanHeaders/incl
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/inclu
## /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/include/Eigen/Core:96:10: f
## #include <complex>
##          ^~~~~~~~~
## 3 errors generated.
## make: *** [foo.o] Error 1
```

```
## Start sampling
```

```
## Warning: There were 36 divergent transitions after warmup. See
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
## to find out why this is a problem and how to eliminate them.
```

```
## Warning: There were 7 transitions after warmup that exceeded the maximum treedepth. Increase max_tre
## http://mc-stan.org/misc/warnings.html#maximum-treedepth-exceeded
```

```
## Warning: Examine the pairs() plot to diagnose sampling problems
```

```r
summary(m1_rt)
```

```
## Warning: There were 36 divergent transitions after warmup. Increasing
## adapt_delta above 0.9 may help. See http://mc-stan.org/misc/
## warnings.html#divergent-transitions-after-warmup
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: lg_rt ~ Task + (Task | Subject) + (Task | Condition)
##    Data: ToM_rt (Number of observations: 3200)
## Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup samples = 4000
##
## Group-Level Effects:
## ~Condition (Number of levels: 4)
##                        Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## sd(Intercept)              0.29      0.23     0.09     0.97 1.00     1094
## sd(TaskLO)                 0.41      0.28     0.13     1.22 1.00     1133
## cor(Intercept,TaskLO)     -0.28      0.49    -0.95     0.78 1.00     1157
##                        Tail_ESS
## sd(Intercept)              1184
## sd(TaskLO)                 1286
## cor(Intercept,TaskLO)       978
##
## ~Subject (Number of levels: 40)
##                        Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## sd(Intercept)              0.26      0.03     0.21     0.34 1.00      745
## sd(TaskLO)                 0.27      0.03     0.21     0.34 1.00      837
## cor(Intercept,TaskLO)     -0.42      0.14    -0.66    -0.12 1.01      720
##                        Tail_ESS
## sd(Intercept)              1108
## sd(TaskLO)                 1530
## cor(Intercept,TaskLO)      1243
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept     7.26      0.18     6.92     7.68 1.00      928     1064
## TaskLO       -0.05      0.24    -0.53     0.47 1.00     1006      897
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.37      0.00     0.37     0.38 1.00     4688     2700
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

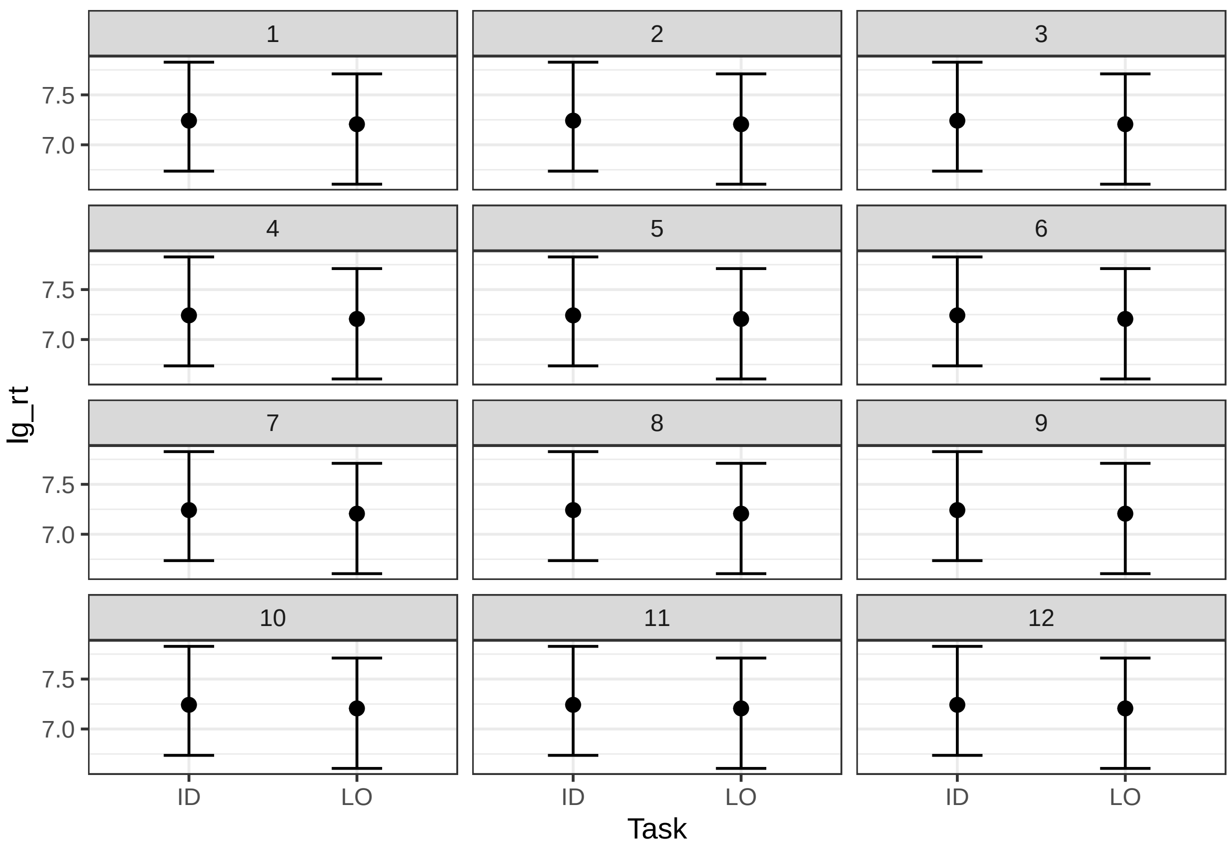
```r
msummary(m1_rt, statistic = "conf.int", statistic_vertical = FALSE)
```

	Model 1
(Intercept)	7.265 [6.916, 7.684]
TaskLO	-0.045 [-0.532, 0.471]
sd___(Intercept)	0.294 [0.087, 0.967]
sd___TaskLO	0.408 [0.133, 1.215]
sd___(Intercept)	0.265 [0.209, 0.337]
sd___TaskLO	0.265 [0.205, 0.341]
cor___(Intercept).TaskLO	-0.279 [-0.949, 0.781]
cor___(Intercept).TaskLO	-0.420 [-0.659, -0.116]
sd___Observation	0.375 [0.366, 0.384]
Num.Obs.	3200
algorithm	sampling
elpd_loo	-1442.757
looic	2885.515
p_loo	85.295
pss	4000.000

4.3 A plot to show the effect of `Task`

```
rand_subj <- sample(unique(ToM_dat$Subject), size = 12)
conditional_effects(m1_rt, type = "pred", re_formula = NULL,
                    conditions = tibble(subj = rand_subj))
```

```
## Warning: The following variables in 'conditions' are not part of the model:
## 'subj'
```



4.4 Interpretation

The results show that the estimate of `Task` is .029 with a 95% CI of [-.445, .463]. This means that the reaction times in Location Task and Identity Task are expected to have a small difference of .029 (after log-tranformation). The 95% CI contains 0, suggesting that this difference is not significant. The estimated sd of `Task` is .388 with a 95% CI of [.132, 1.119]. Since I take random slopes into consideration, the estimated sd of the slope between `Subject` and `Task` is .264 with a 95% CI of [.205, .339]. This indicates that different subjects have different slopes, which means that they have various ranges of reaction time.

Analysis of Accuracy

1. Data Preprocessing

For each cell (`Task` x `Condition`), each participant will be measured 10 times. In a single trial, if they judge correctly, they will get 1, if not, they will get 0. Thus, I plan to use a number calculated by n/10 to represent their accuracy rate for each cell. In this case, each participant has a score ranging from 0 to 1 for each cell (`Task` x `Condition`). Log transformation is also performed.

```r
head(ToM_err)
```

```
## # A tibble: 6 x 4
##   Subject Condition   err Task
##     <int> <chr>     <int> <chr>
## 1       1 AD_p          1 ID
## 2       1 AU_p          1 ID
## 3       1 AD_a          1 ID
## 4       1 AU_a          1 ID
## 5       1 AD_p          0 LO
## 6       1 AU_p          1 LO
```

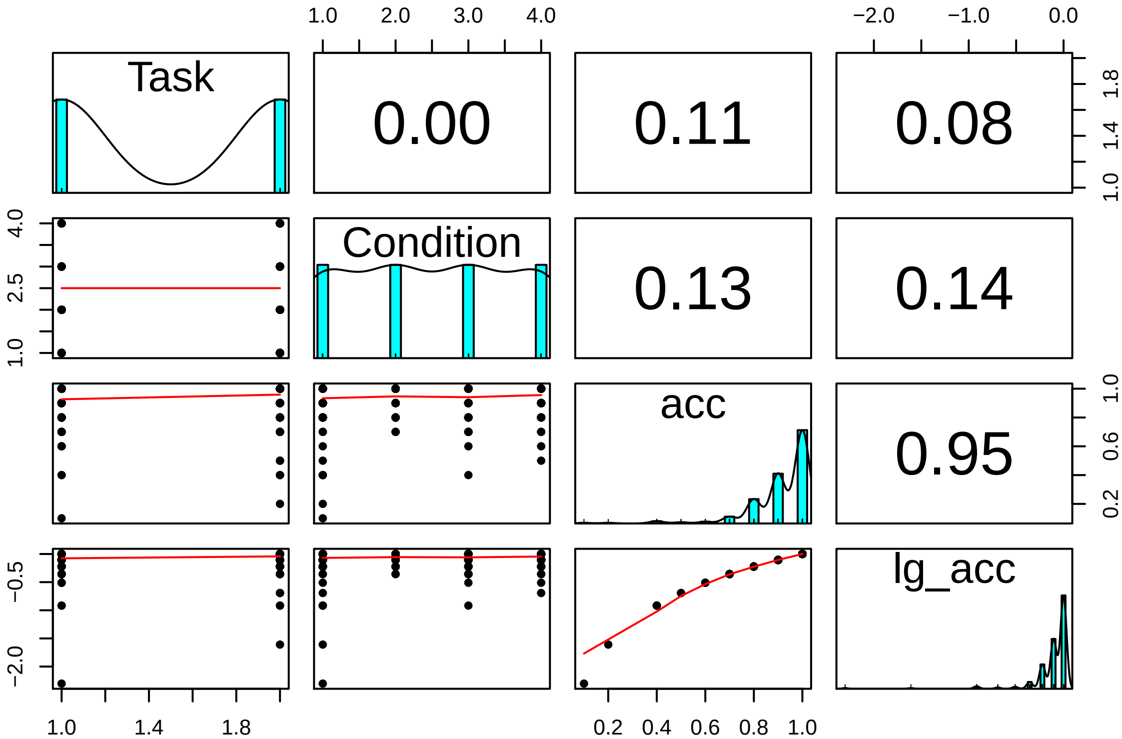
```r
ToM_acc <- as.data.frame.table(
  tapply(ToM_err$err,list(ToM_err$Subject,ToM_err$Task,ToM_err$Condition),mean))
colnames(ToM_acc) <- c("Subject","Task","Condition","acc")

# Log transformation for acc
ToM_acc$lg_acc <- log(ToM_acc$acc)
head(ToM_acc)
```

```
##   Subject Task Condition acc     lg_acc
## 1       1   ID      AD_a 0.9 -0.1053605
## 2       2   ID      AD_a 0.9 -0.1053605
## 3       3   ID      AD_a 0.9 -0.1053605
## 4       4   ID      AD_a 0.9 -0.1053605
## 5       5   ID      AD_a 0.9 -0.1053605
## 6       6   ID      AD_a 0.8 -0.2231436
```

2. Data Exploration

```r
pairs.panels(ToM_acc[ , -1],
             ellipses = FALSE)
```



3. Unconditional model with random intercepts First, I run an unconditional model with random intercepts of both `Subject` and `Task`.

```
m0_acc <- lmer(lg_acc ~ (1 | Subject) + (1 | Task), data = ToM_acc)
vc_m0_acc <- as.data.frame(VarCorr(m0_acc))

# Proportion of variance at the within-cell level
icc_e_acc <- vc_m0_acc$vcov[3] / sum(vc_m0_acc$vcov)

# ICC/Deff (Subject; cluster size = 2)
icc_subj_acc <- vc_m0_acc$vcov[1] / sum(vc_m0_acc$vcov)
c("ICC(subj_acc)" = icc_subj_acc,
  "Deff(subj_acc)" = 1 + (4 * icc_subj_acc))
```

```
##  ICC(subj_acc) Deff(subj_acc)
##     0.06356053     1.25424213
```

```
# ICC/Deff (Task; cluster size = 40)
icc_task_acc <- vc_m0_acc$vcov[2] / sum(vc_m0_acc$vcov)
c("ICC(Task_acc)" = icc_task_acc, "Deff(Task_acc)" = icc_e_acc + 40 * icc_task_acc)
```

```
##  ICC(Task_acc) Deff(Task_acc)
##    0.007710037    1.237130892
```

```
c("ICC(Subject_acc + Task_acc)" = sum(vc_m0_acc$vcov[1:2]) / sum(vc_m0_acc$vcov))
```

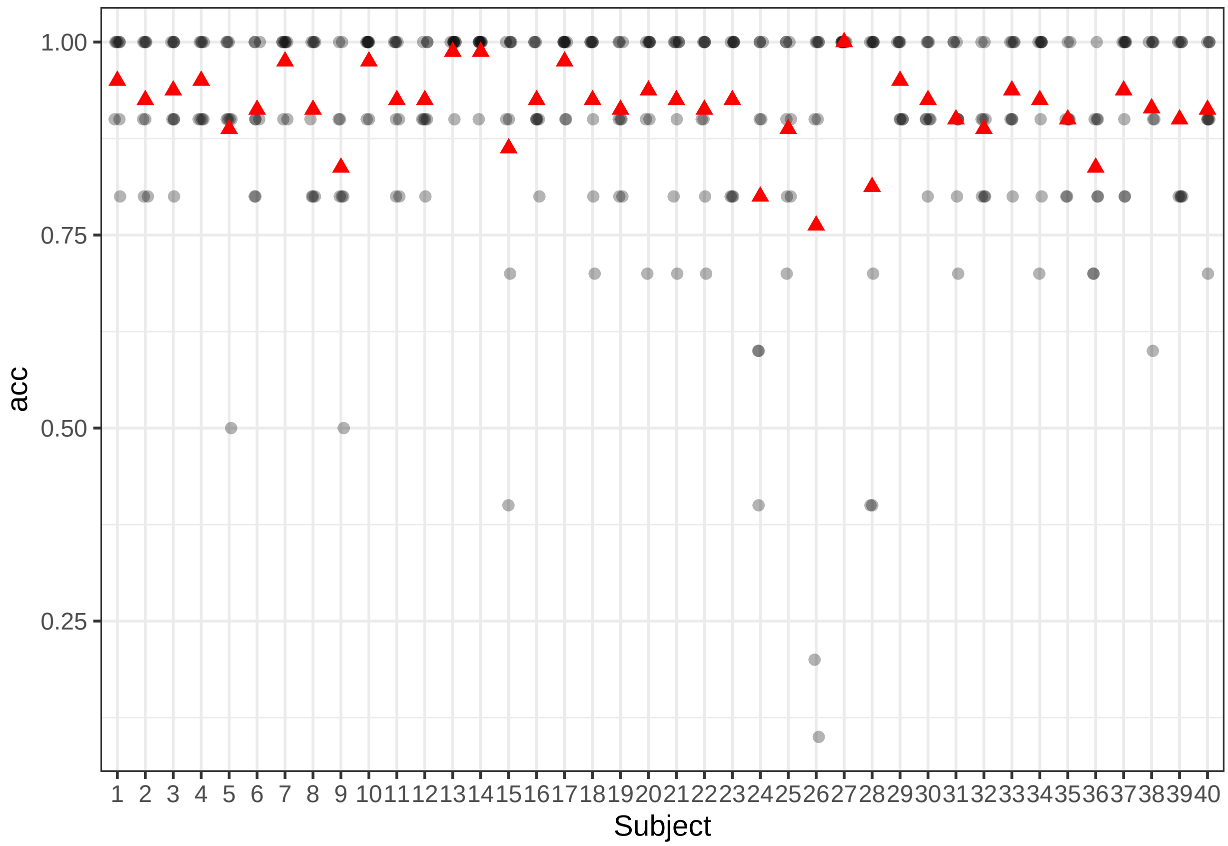
```
## ICC(Subject_acc + Task_acc)
##                  0.07127057
```

The results show that the ICC of `Subject` is .064 with the design effect of 1.254. This means that we can expect a very week correlation between two randomly drawn units from the same subject. It appears that accuracy is less individual than reaction time. Next, the ICC of `Task` is .084 with the design effect of 1.237. Together, the ICC is .071.
The variations across persons, acorss tasks, and across conditions are plotted as below.

```r
# Variation across persons
sub_ids <- unique(ToM_acc$Subject)
(p_set <- ToM_acc %>%
    filter(Subject %in% sub_ids) %>%
    ggplot(aes(x = Subject, y = acc)) +
    geom_jitter(height = 0, width = 0.1, alpha = 0.3) +
    scale_x_discrete(breaks = sub_ids, labels = sub_ids) +
    # Add subject means
    stat_summary(
      fun = "mean",
      geom = "point",
      col = "red",
      shape = 17,
      # use triangles
      size = 2)
)
```

```
## Warning: Removed 1 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```



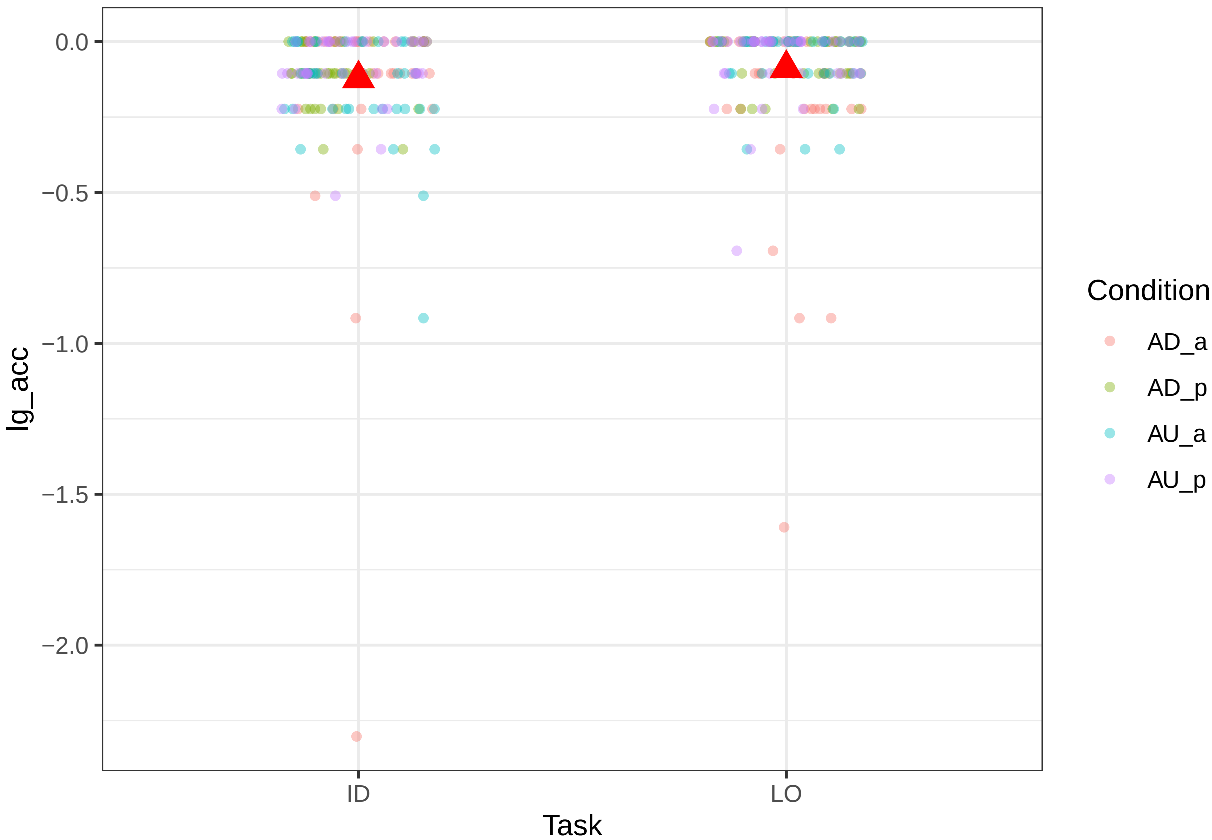

```r
par(mfrow=c(1,2))

# Variation across tasks
task_ids <- unique(ToM_acc$Task)
ggplot(aes(x = Task, y = lg_acc, color=Condition),data = ToM_acc) +
  geom_jitter(height = 0, width = 0.18, alpha = 0.4, size = 1.2) +
  stat_summary(
```

```
    fun = "mean",
    geom = "point",
    col = "red",
    shape = 17,
    size = 4)
```

```
## Warning: Removed 1 rows containing non-finite values (stat_summary).
```

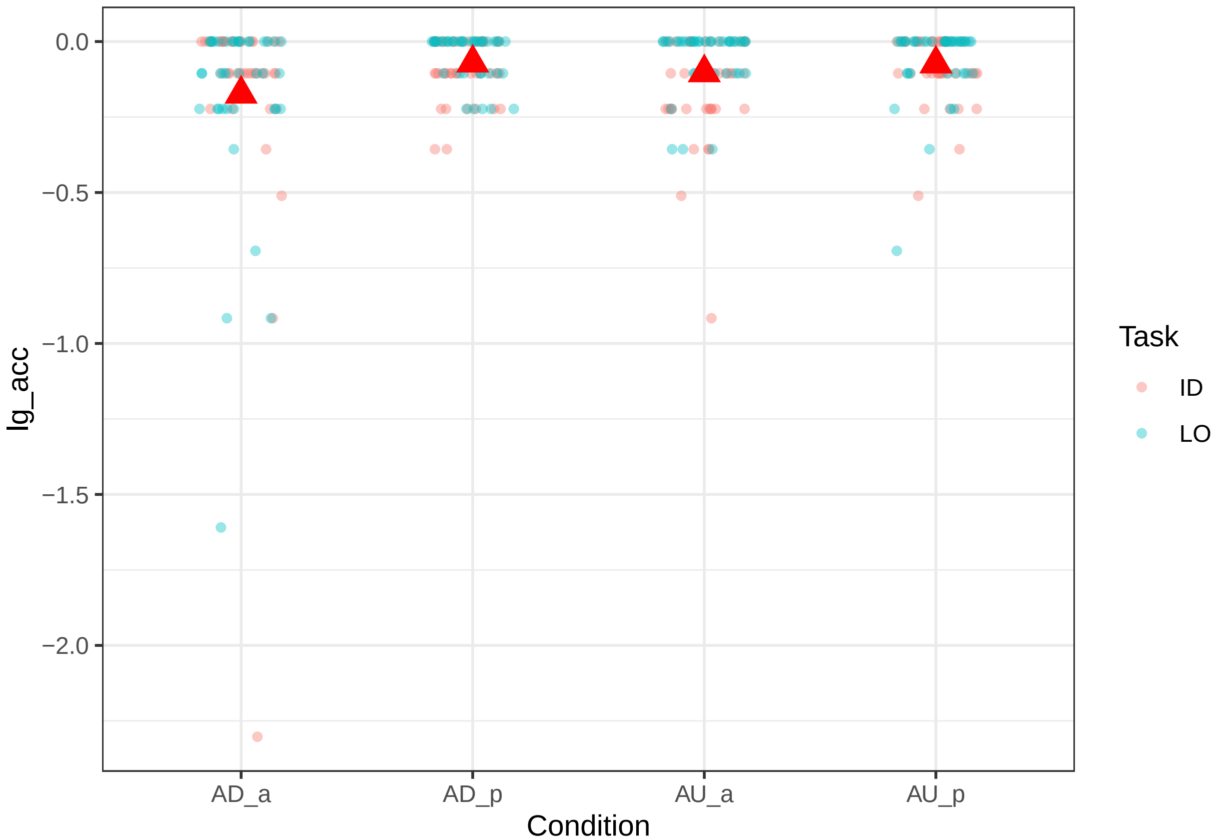
```
## Warning: Removed 1 rows containing missing values (geom_point).
```




```
# Variation across conditions
condition_ids <- unique(ToM_acc$Condition)
ggplot(aes(x = Condition, y = lg_acc, color=Task),data = ToM_acc) +
  geom_jitter(height = 0, width = 0.18, alpha = 0.4, size = 1.2) +
  stat_summary(
    fun = "mean",
    geom = "point",
    col = "red",
    shape = 17,
    size = 4)
```

```
## Warning: Removed 1 rows containing non-finite values (stat_summary).
```

```
## Warning: Removed 1 rows containing missing values (geom_point).
```




```
par(mfrow=c(1,1))
```

4. Judgement

Similarly, the experimental manipulation is `Task`, which has two values: ID and LO. I'll make Identity task the reference group by making the variable a factor with Identity task as the first category.

```
ToM_acc <- ToM_acc %>%
  mutate(Task = factor(Task, levels = c("ID", "LO")))
```

5. Modeling for `acc`

5.1 Model Equations

Repeated-Measure level (Lv 1):

$$\text{lg acc}_{i(j,k)} = \beta_{0(j,k)} + e_{ijk}$$

Lv 2:

$$\beta_{0(j,k)} = \gamma_{00} + \beta_{1j}\text{Task}_{ik} + \beta_{2j}\text{Condition}_{ik} + \beta_{3j}\text{Task}_{ik} \times \text{Condition}_{ik} + u_{0j} + v_{0k}$$

Condition level (Lv 2a) random slopes

$$\beta_{1j} = \gamma_{10} + +u_{1j}$$
$$\beta_{2j} = \gamma_{20} + u_{2j}$$
$$\beta_{3j} = \gamma_{30} + u_{3j}$$

Combined equations

$$
\begin{aligned}
\lg \mathrm{acc}_{i(j,k)} = \gamma_{00} & \\
& + \gamma_{10}\mathrm{Task}_{ik} + \gamma_{20}\mathrm{Condition}_{ik} + \gamma_{30}\mathrm{Condition}_{ik} \times \mathrm{Task}_{ik} + \\
& + u_{0j} + u_{1j}\mathrm{Task}_{ik} + u_{2j}\mathrm{Condition}_{ik} + u_{3j}\mathrm{Task}_{ik} \times \mathrm{Condition}_{ik} \\
& + v_{0k} + e_{ijk}
\end{aligned}
$$

5.2 Fit a Model

In order to estimate the effect of `Task` on `acc`, I fit another Bayesian multilevel model here.

```
m1_acc <- brm(lg_acc ~ Task + (Task | Subject) + (Task | Condition),
              data = ToM_acc,
              control = list(adapt_delta = .9),
              cores = 2)
```

```
## Warning: Rows containing NAs were excluded from the model.

## Compiling Stan program...

## Trying to compile a simple C file

## Running /Library/Frameworks/R.framework/Resources/bin/R CMD SHLIB foo.c
## clang -mmacosx-version-min=10.13 -I"/Library/Frameworks/R.framework/Resources/include" -DNDEBUG   -I
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/StanHeaders/incl
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/inclu
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/inclu
## /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/include/Eigen/src/Core/util/
## namespace Eigen {
## ^
## /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/include/Eigen/src/Core/util/
## namespace Eigen {
##                ^
##                ;
## In file included from <built-in>:1:
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/StanHeaders/incl
## In file included from /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/inclu
## /Library/Frameworks/R.framework/Versions/4.0/Resources/library/RcppEigen/include/Eigen/Core:96:10: fa
## #include <complex>
##          ^~~~~~~~~
## 3 errors generated.
## make: *** [foo.o] Error 1

## Start sampling

## Warning: There were 48 divergent transitions after warmup. See
## http://mc-stan.org/misc/warnings.html#divergent-transitions-after-warmup
## to find out why this is a problem and how to eliminate them.

## Warning: Examine the pairs() plot to diagnose sampling problems
```

```
summary(m1_acc)
```

```
## Warning: There were 48 divergent transitions after warmup. Increasing
## adapt_delta above 0.9 may help. See http://mc-stan.org/misc/
## warnings.html#divergent-transitions-after-warmup
```

```
##  Family: gaussian
##   Links: mu = identity; sigma = identity
## Formula: lg_acc ~ Task + (Task | Subject) + (Task | Condition)
##    Data: ToM_acc (Number of observations: 319)
## Samples: 4 chains, each with iter = 2000; warmup = 1000; thin = 1;
##          total post-warmup samples = 4000
##
## Group-Level Effects:
## ~Condition (Number of levels: 4)
##                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## sd(Intercept)             0.07      0.08     0.00     0.29 1.00      803
## sd(TaskLO)                0.09      0.09     0.00     0.35 1.00      923
## cor(Intercept,TaskLO)     0.06      0.57    -0.92     0.96 1.00     1673
##                       Tail_ESS
## sd(Intercept)             1025
## sd(TaskLO)                 529
## cor(Intercept,TaskLO)     1231
##
## ~Subject (Number of levels: 40)
##                       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS
## sd(Intercept)             0.05      0.02     0.01     0.10 1.01      936
## sd(TaskLO)                0.02      0.02     0.00     0.06 1.00     2376
## cor(Intercept,TaskLO)    -0.14      0.57    -0.97     0.93 1.00     3761
##                       Tail_ESS
## sd(Intercept)              732
## sd(TaskLO)                1780
## cor(Intercept,TaskLO)     2594
##
## Population-Level Effects:
##           Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## Intercept    -0.12      0.05    -0.22    -0.02 1.00     1200      992
## TaskLO        0.04      0.06    -0.08     0.17 1.00     1077      413
##
## Family Specific Parameters:
##       Estimate Est.Error l-95% CI u-95% CI Rhat Bulk_ESS Tail_ESS
## sigma     0.20      0.01     0.19     0.22 1.00     3011     2670
##
## Samples were drawn using sampling(NUTS). For each parameter, Bulk_ESS
## and Tail_ESS are effective sample size measures, and Rhat is the potential
## scale reduction factor on split chains (at convergence, Rhat = 1).
```

```r
msummary(m1_acc, statistic = "conf.int", statistic_vertical = FALSE)
```

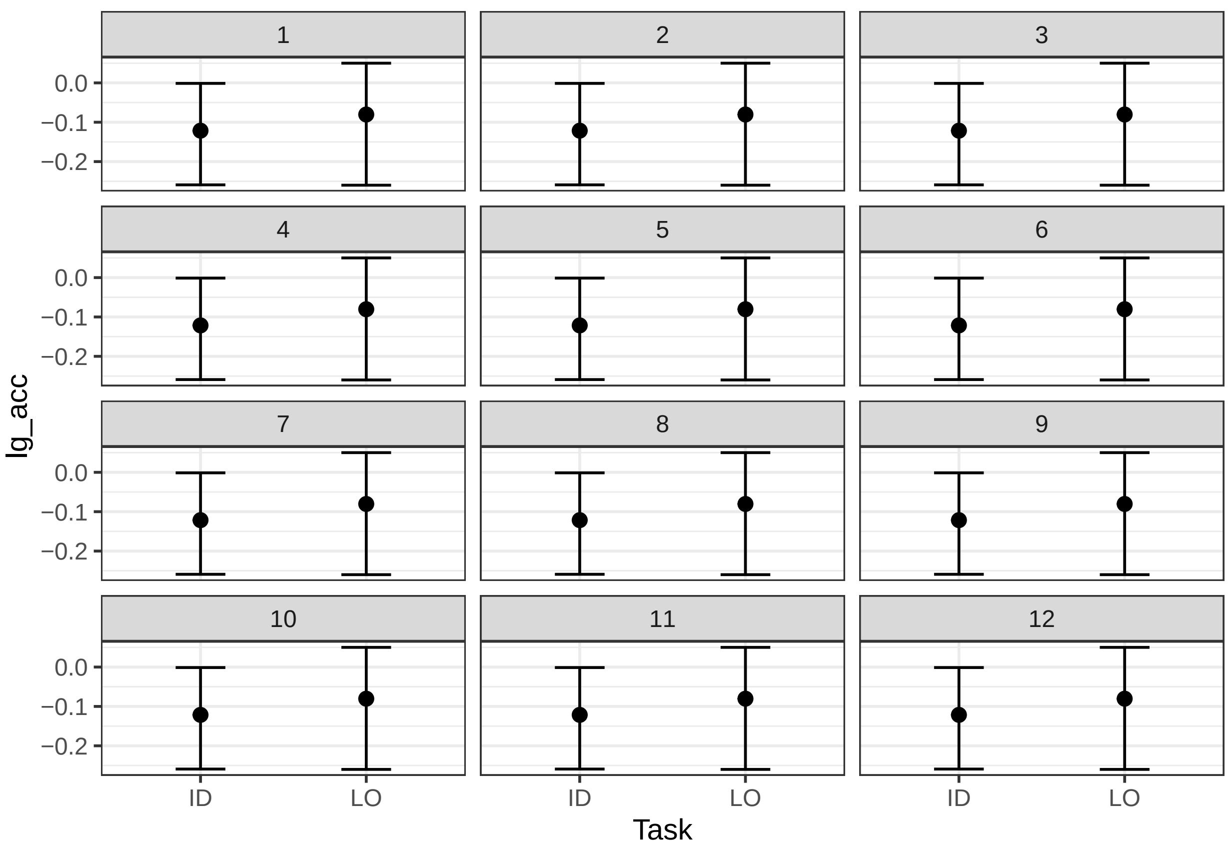
```
## Warning: Found 2 observations with a pareto_k > 0.7 in model 'x'. It is
## recommended to set 'moment_match = TRUE' in order to perform moment matching for
## problematic observations.
```

	Model 1
(Intercept)	-0.121 [-0.215, -0.017]
TaskLO	0.038 [-0.082, 0.171]
sd___(Intercept)	0.072 [0.003, 0.295]
sd___TaskLO	0.089 [0.003, 0.347]
sd___(Intercept)	0.054 [0.009, 0.095]
sd___TaskLO	0.020 [0.001, 0.057]
cor___(Intercept).TaskLO	0.061 [-0.917, 0.962]
cor___(Intercept).TaskLO	-0.144 [-0.969, 0.934]
sd___Observation	0.201 [0.185, 0.219]
Num.Obs.	319
algorithm	sampling
elpd_loo	37.549
looic	-75.099
p_loo	41.288
pss	4000.000

5.3 A plot to show the effect of `Task`

```r
rand_subj <- sample(unique(ToM_dat$Subject), size = 12)
conditional_effects(m1_acc, type = "pred", re_formula = NULL,
                    conditions = tibble(subj = rand_subj))
```

```
## Warning: The following variables in 'conditions' are not part of the model:
## 'subj'
```



5.4 Interpretation As for accuracy, the estimate of `Task` is .034 with a 95% CI of [-.090, .156]. This

means that the accuracy in Location Task and in Identity Task are expected to have a small difference of .09 (after log-tranformation). The 95% CI contains 0, suggesting that this difference is not significant. The estimated sd of `Task` is .086 with a 95% CI of [.003, .336]. Taking random slopes into consideration, the estimated sd of the slope between `Subject` and `Task` is .020 with a 95% CI of [.001, .059]. This indicates that different subjects have different slopes, which means that they have various ranges of accuracy. Compared with reaction time, there are less variance in accuracy, which can also be observed in the graph. This is because that the data for accuracy is binary originally, so subjects' accuracy will not have much difference as they have in reaction time.