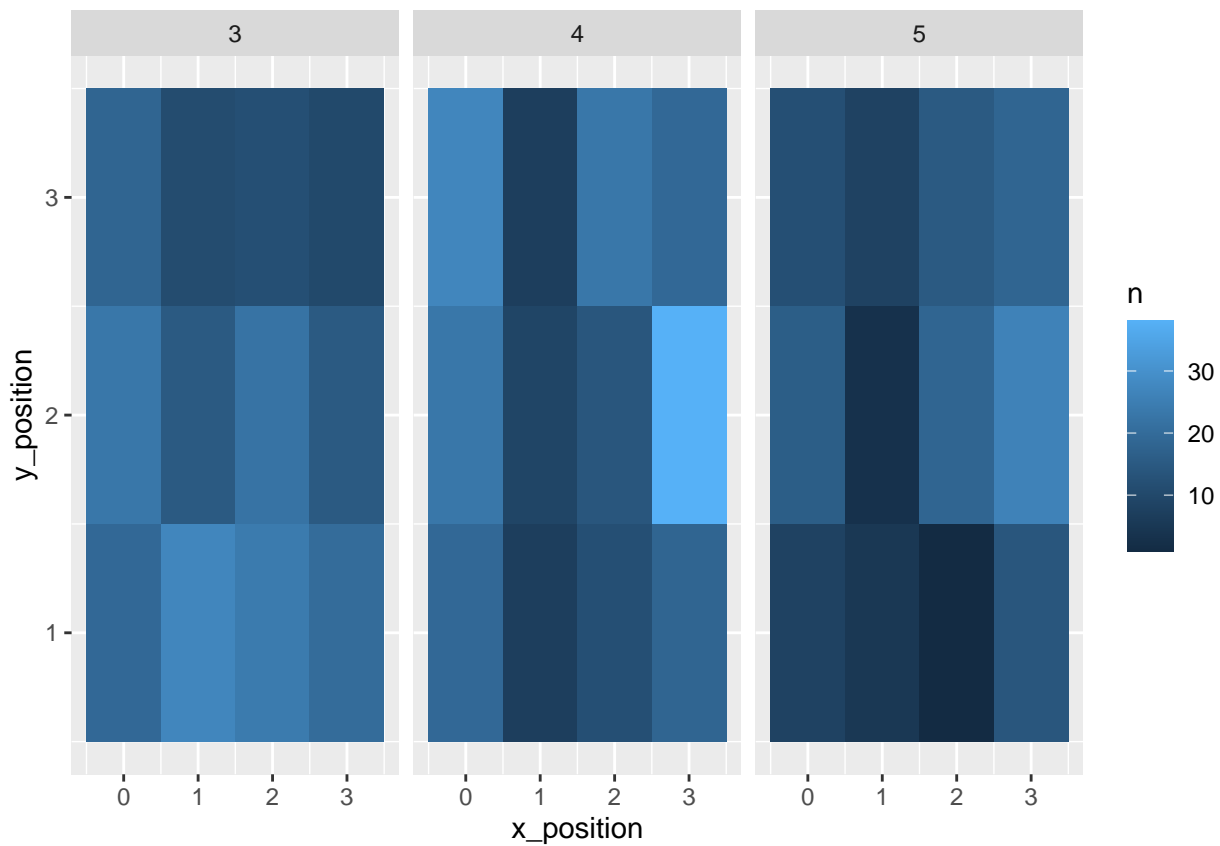


## pilot\_child\_analysis

2025-07-24

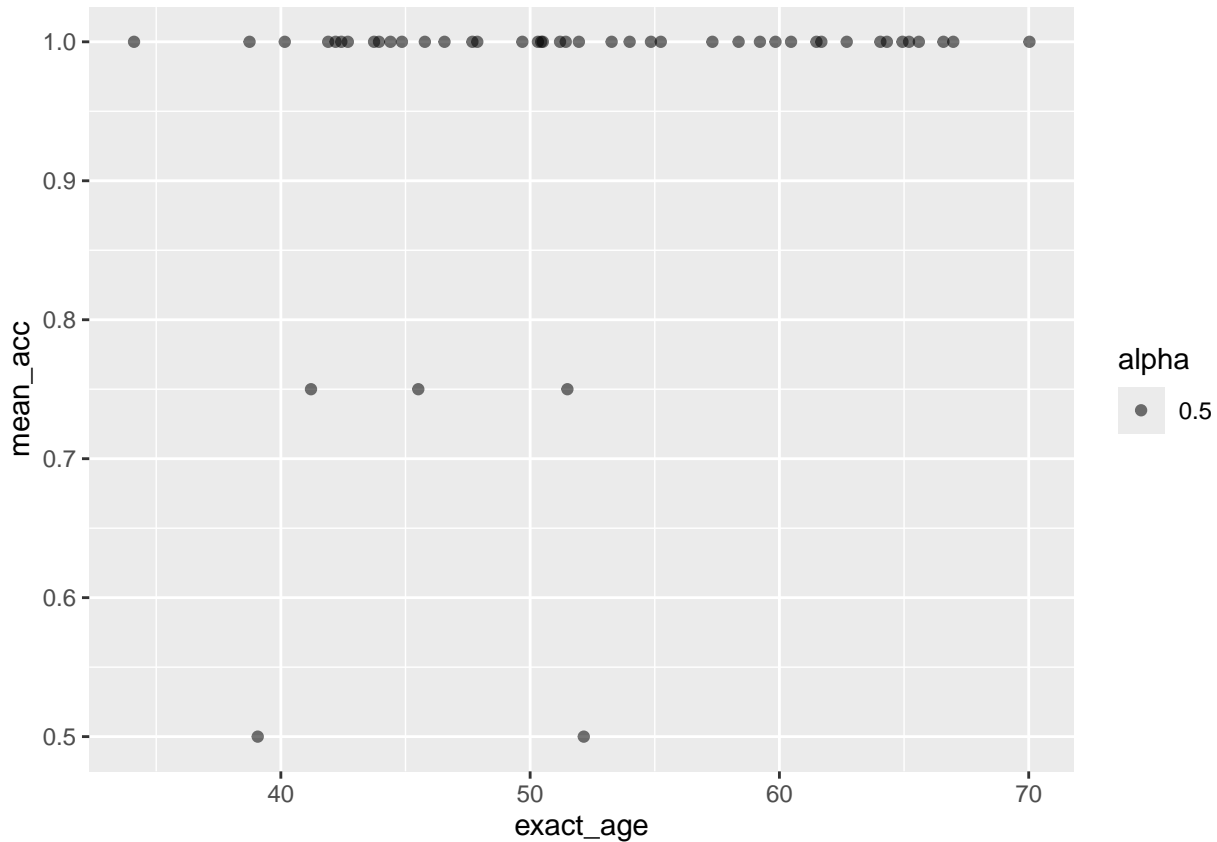
We currently have 48 child participants in the study: 18 three-year-olds, 18 four-year-olds, and 12 five-year-olds.

```
data %>%  
  mutate(x_position = (image_location + 1) %% 4,  
         y_position = case_when(image_location <= 3 ~ 3,  
                                image_location <= 7 ~ 2,  
                                .default = 1)) %>%  
  count(participant_age, x_position, y_position) %>%  
  ggplot(aes(x = x_position, y = y_position, fill = n)) +  
  geom_tile() +  
  facet_wrap(~participant_age)
```



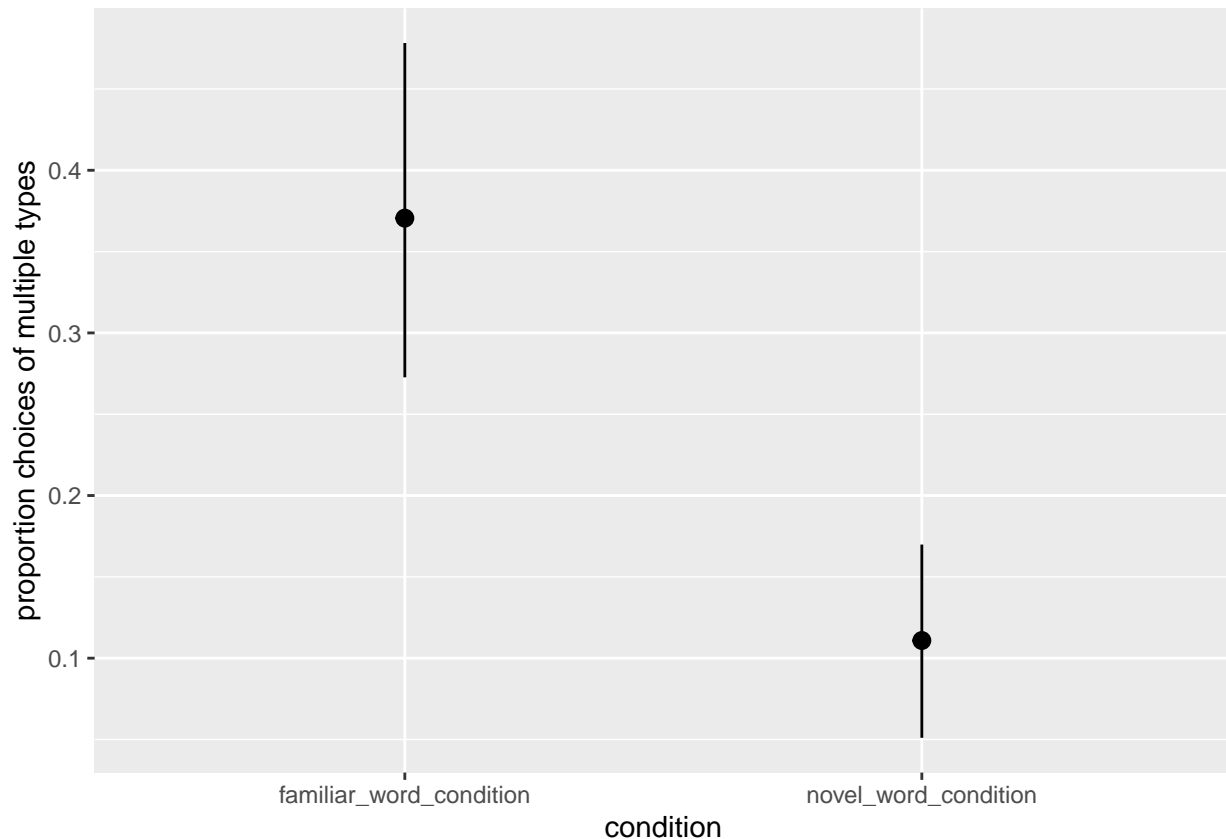
Heatmap of where on the screen children tapped, by age. Possibly a slight bias toward the left and right edges and middle row (likely where their hands rest). Image positions were randomized so this isn't a confound.

```
data %>%
  filter(trial_number <= 1) %>%
  mutate(accuracy = if_else(str_remove(word, "s") == stimulus_subclass, 1, 0)) %>%
  group_by(participant_id, exact_age) %>%
  summarise(mean_acc = mean(accuracy)) %>%
  ggplot(aes(x = exact_age, y = mean_acc, alpha = 0.5)) +
  geom_point(height = 0, width = 0.2)
```



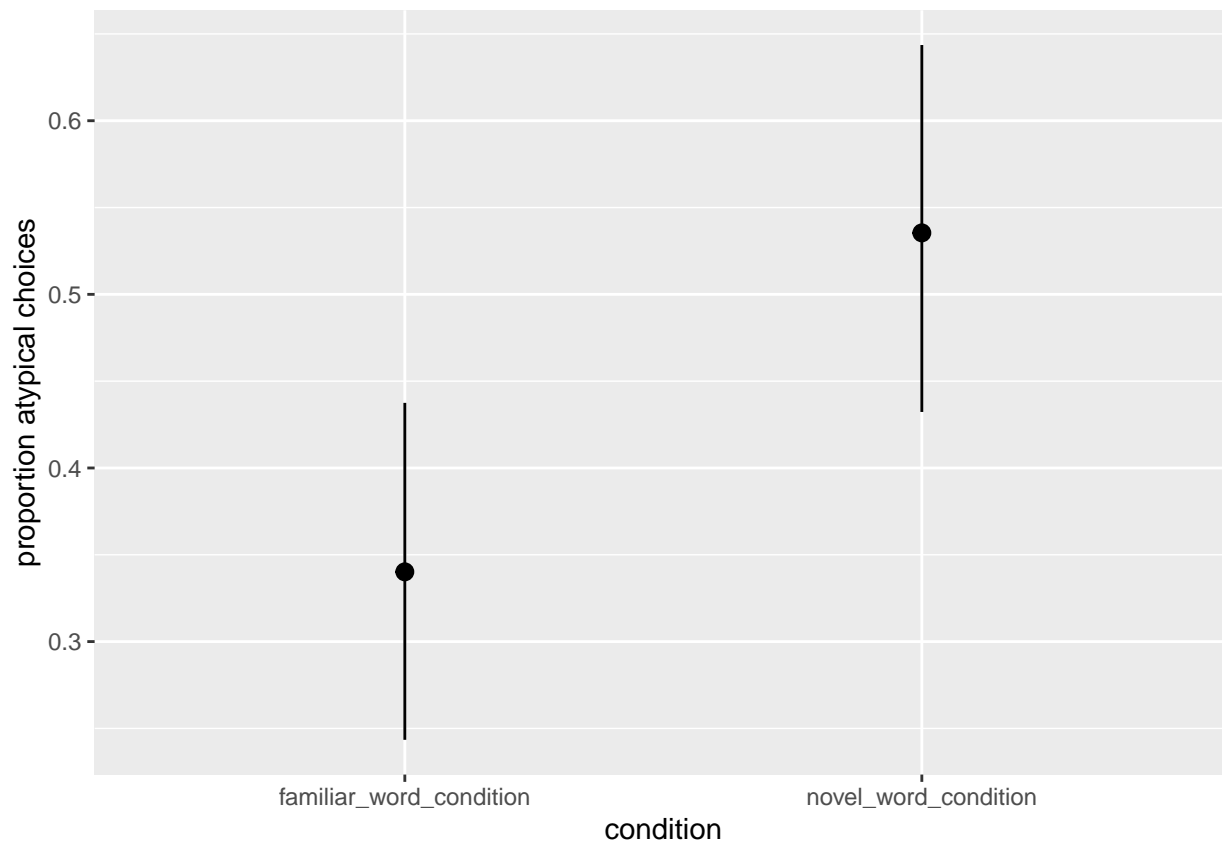
Accuracy on practice trials (“Tap on two carrots” and “Tap on two apples”). Almost all children choose 100% accurately.

```
data %>%
  filter(trial_number > 1) %>%
  group_by(participant_id, condition, trial_number) %>%
  summarise(n_distinct = n_distinct(stimulus_subclass) - 1) %>%
  ungroup() %>%
  group_by(condition) %>%
  tidyboot_mean(n_distinct) %>%
  ungroup() %>%
  ggplot(aes(x = condition, y = mean)) +
  geom_pointrange(aes(ymin = ci_lower, ymax = ci_upper)) +
  ylab("proportion choices of multiple types")
```



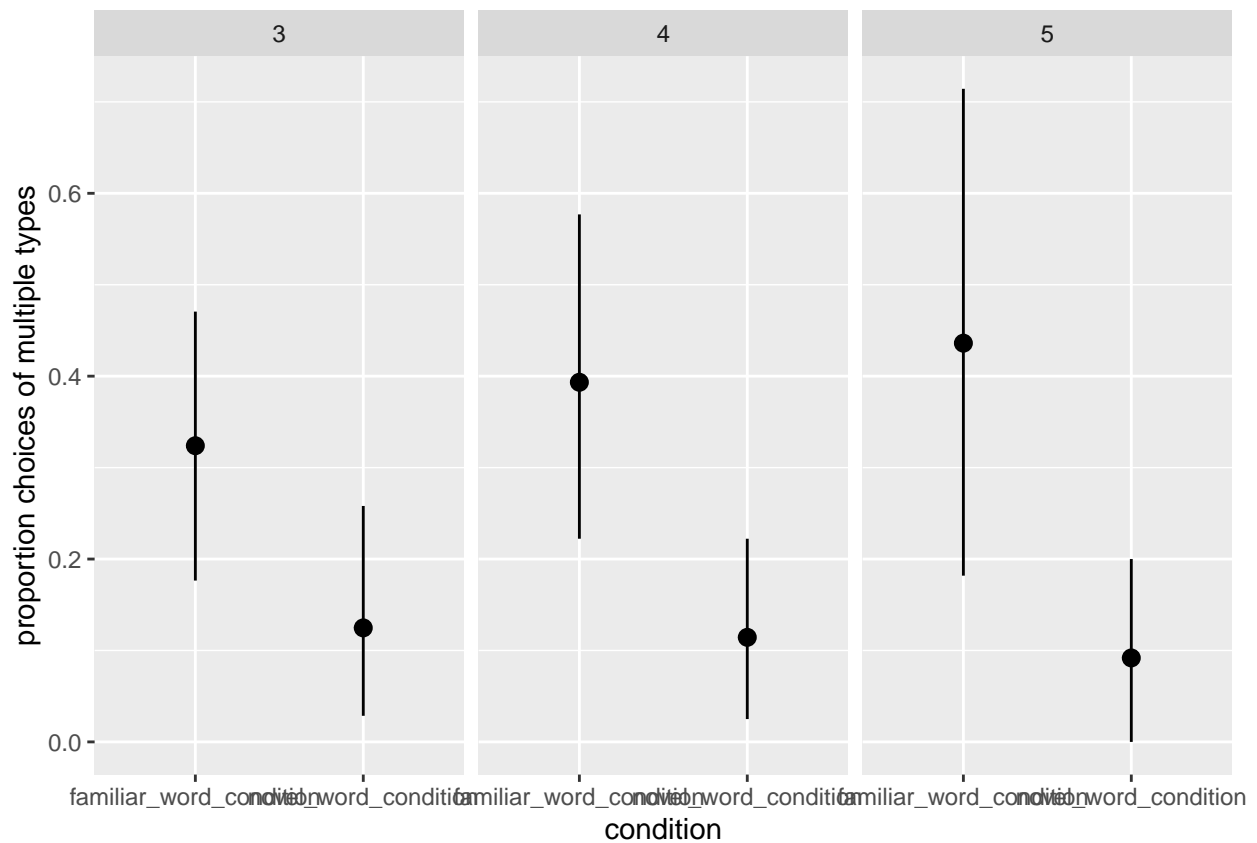
Choices of multiple subtypes of stimuli. Our prediction is that children choose multiple subtypes more often when prompted with a familiar word (sampling across the category) and choose one subtype more often when prompted with a novel word (inferring the novel word refers to a specific subtype of the category). Children are currently patterning in line with our prediction.

```
data %>%
  filter(trial_number > 1) %>%
  group_by(condition, participant_id) %>%
  summarise(prop_atypical = sum(typicality)/n()) %>%
  ungroup() %>%
  group_by(condition) %>%
  tidyboot_mean(prop_atypical) %>%
  ungroup() %>%
  ggplot(aes(x = condition, y = mean)) +
  geom_pointrange(aes(ymin = ci_lower, ymax = ci_upper)) +
  ylab("proportion atypical choices")
```

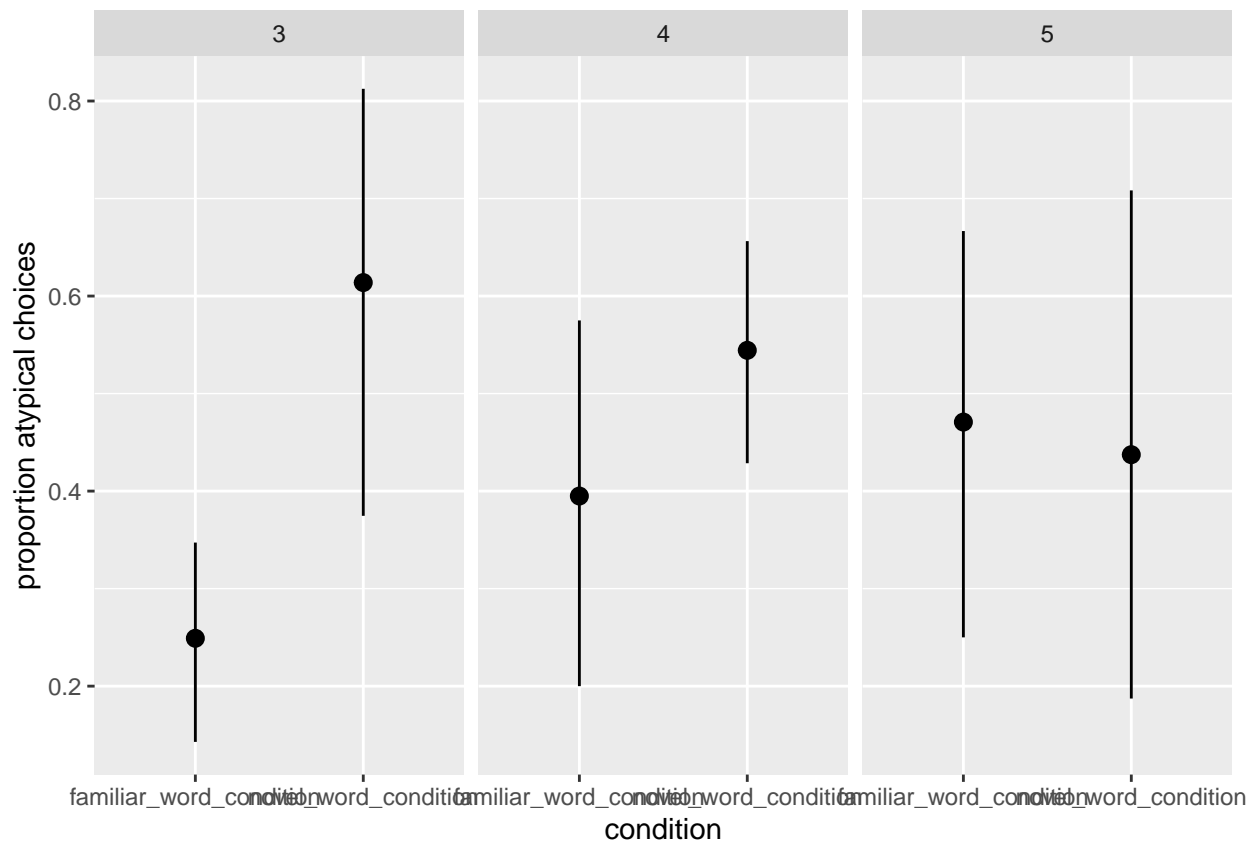


Choices of atypical stimuli. Our prediction is that children will choose more typical stimuli when prompted with a familiar word, and will choose more atypical stimuli when prompted with a novel word (inferring the novel word refers to an atypical subtype of the category). Children are patterning in line with our prediction.

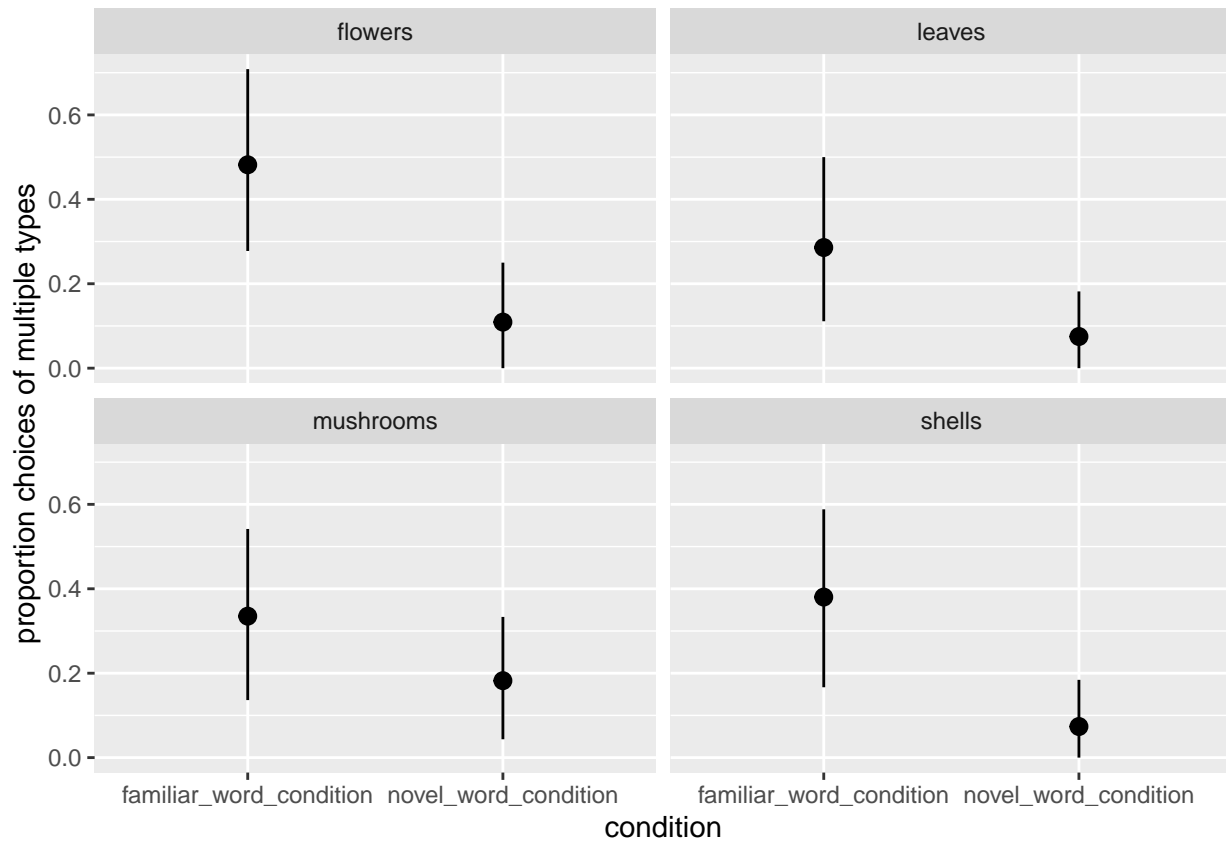
```
data %>%
  filter(trial_number > 1) %>%
  group_by(participant_id, condition, category, participant_age, trial_number) %>%
  summarise(n_distinct = n_distinct(stimulus_subclass) - 1) %>%
  ungroup() %>%
  group_by(condition, participant_age) %>%
  tidyboot_mean(n_distinct) %>%
  ungroup() %>%
  ggplot(aes(x = condition, y = mean)) +
  geom_pointrange(aes(ymin = ci_lower, ymax = ci_upper)) +
  ylab("proportion choices of multiple types") +
  facet_wrap(~participant_age)
```



```
data %>%
  filter(trial_number > 1) %>%
  group_by(condition, participant_age, participant_id) %>%
  summarise(prop_atypical = sum(typicality)/n()) %>%
  ungroup() %>%
  group_by(condition, participant_age) %>%
  tidyboot_mean(prop_atypical) %>%
  ungroup() %>%
  ggplot(aes(x = condition, y = mean)) +
  geom_pointrange(aes(ymin = ci_lower, ymax = ci_upper)) +
  ylab("proportion atypical choices") +
  facet_wrap(~participant_age)
```

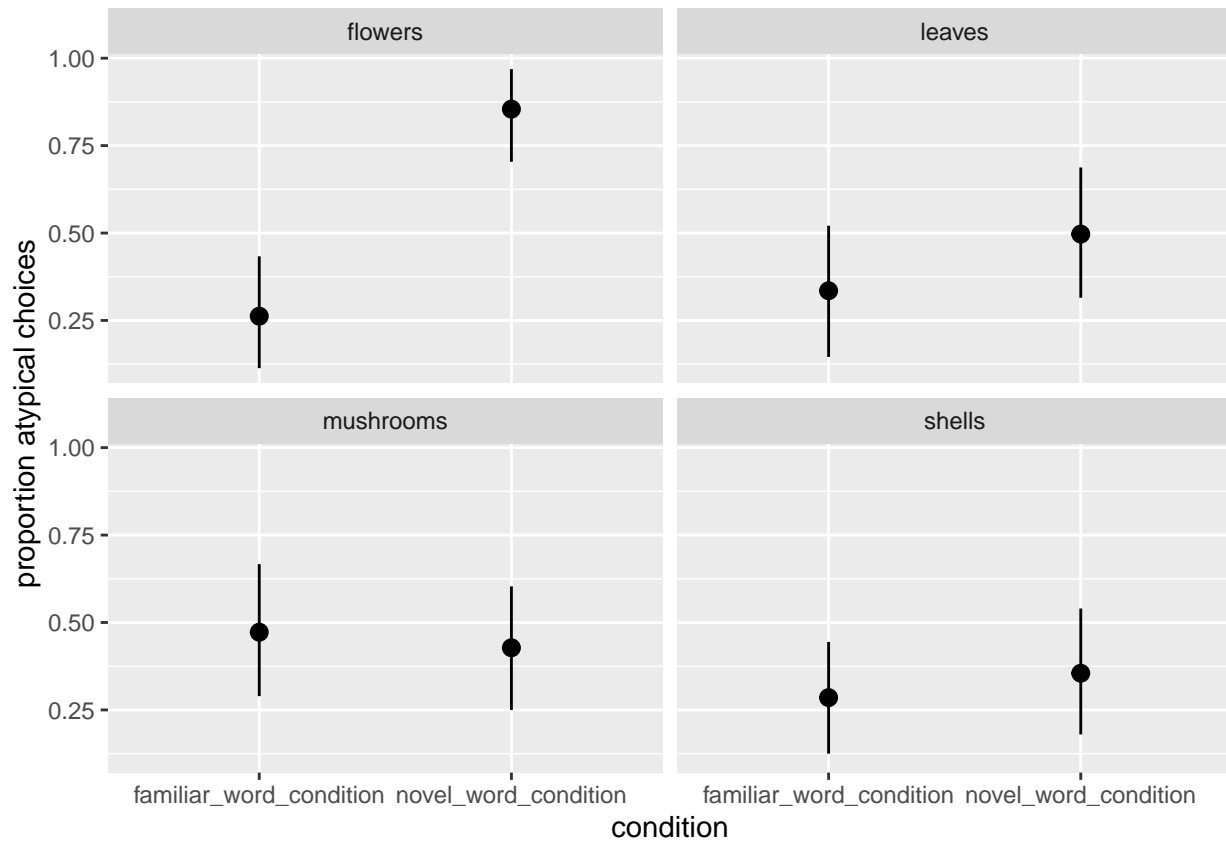


```
data %>%
  filter(trial_number > 1) %>%
  group_by(participant_id, condition, category, trial_number) %>%
  summarise(n_distinct = n_distinct(stimulus_subclass) - 1) %>%
  ungroup() %>%
  group_by(condition, category) %>%
  tidyboot_mean(n_distinct) %>%
  ungroup() %>%
  ggplot(aes(x = condition, y = mean)) +
  geom_pointrange(aes(ymin = ci_lower, ymax = ci_upper)) +
  facet_wrap(~category) +
  ylab("proportion choices of multiple types")
```



Choices of multiple types, by stimulus item.

```
data %>%
  filter(trial_number > 1) %>%
  group_by(condition, participant_id, category) %>%
  summarise(prop_atypical = sum(typicality)/n()) %>%
  ungroup() %>%
  group_by(condition, category) %>%
  tidyboot_mean(prop_atypical) %>%
  ungroup() %>%
  ggplot(aes(x = condition, y = mean)) +
  geom_pointrange(aes(ymin = ci_lower, ymax = ci_upper)) +
  facet_wrap(~category) +
  ylab("proportion atypical choices")
```



Choices of atypical items, by stimulus item. Mushrooms are potentially a difficult item.

```
mean_age <- data %>%
  distinct(participant_id, exact_age) %>%
  summarise(mean_age = mean(exact_age, na.rm = TRUE)) %>%
  pull()

model_data <- data %>%
  filter(trial_number > 1) %>%
  group_by(participant_id, exact_age, condition, category, trial_number) %>%
  summarise(n_distinct = n_distinct(stimulus_subclass) - 1,
            n_atypical = sum(typicality)) %>%
  ungroup() %>%
  mutate(participant_id = as.factor(participant_id),
         exact_age = exact_age - mean_age)

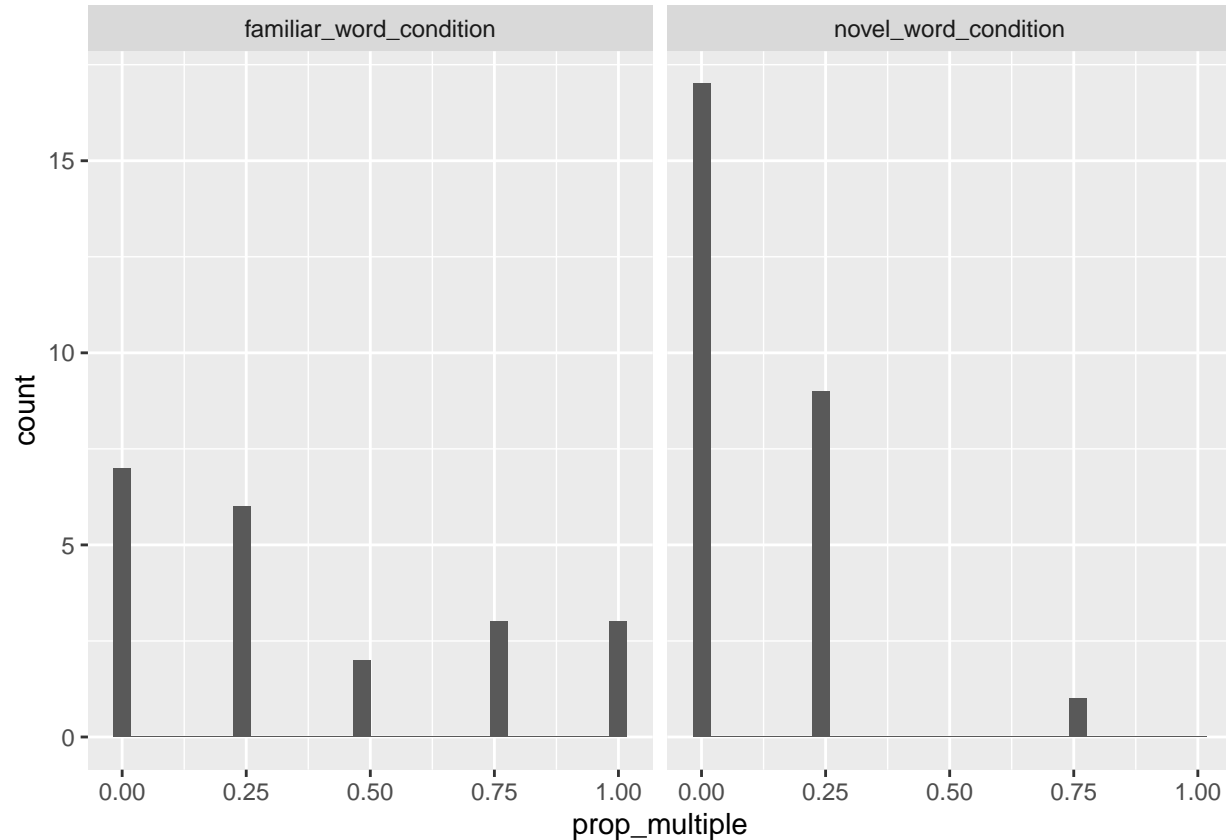
glmer(cbind(n_atypical, 2-n_atypical) ~ condition * exact_age + (1 | participant_id) + (1 | category),
      data = model_data) %>%
  tidy()
```

```
## # A tibble: 6 x 7
##   effect  group      term      estimate std.error statistic  p.value
##   <chr>   <chr>    <chr>      <dbl>    <dbl>    <dbl>    <dbl>
## 1 fixed  <NA>    (Intercept) -0.848    0.386    -2.20    0.0281
## 2 fixed  <NA>    conditionnovel_~ 1.03    0.396     2.60    0.00942
## 3 fixed  <NA>    exact_age      0.0354   0.0326     1.09    0.278
## 4 fixed  <NA>    conditionnovel_~ -0.0698  0.0435    -1.60    0.109
```



```
## 5 ran_pars participant_id sd__(Intercept) 1.04 NA NA NA
## 6 ran_pars category sd__(Intercept) 0.481 NA NA NA
```

```
model_data %>%
  group_by(participant_id, exact_age, condition) %>%
  summarise(prop_multiple = mean(n_distinct)) %>%
  ggplot(aes(x = prop_multiple)) +
  geom_histogram() +
  facet_wrap(~condition)
```



```
glmer(n_distinct ~ condition * exact_age + (1 | category) + (1 | participant_id), family = "binomial",
  data = model_data) %>%
  tidy()
```

```
## # A tibble: 6 x 7
##   effect   group      term      estimate std.error statistic  p.value
##   <chr>   <chr>    <chr>      <dbl>    <dbl>    <dbl>    <dbl>
## 1 fixed   <NA>    (Intercept) -9.45e-1  0.427    -2.21    0.0270
## 2 fixed   <NA>    conditionnovel_~ -1.71e+0  0.620    -2.76    0.00577
## 3 fixed   <NA>    exact_age    -2.18e-2  0.0459   -0.475    0.635
## 4 fixed   <NA>    conditionnovel_~ -2.97e-2  0.0664   -0.447    0.655
## 5 ran_pars participant_id sd__(Intercept) 1.29e+0  NA      NA      NA
## 6 ran_pars category    sd__(Intercept) 1.69e-5  NA      NA      NA
```