Landmark analyses

Last updated: 2018-06-04

Contents

Setup

Load libraries

```
library(tidyverse)
library(broom)
library(knitr)
library(kableExtra)
library(lme4)
library(merTools)
```

Load data

```
learners <- read_csv("./landmarks_stress_la_lb_ss.csv")
heritage <- read_csv("./landmarks_stress_la_hs_ss.csv")
wm_df_learners <- read_csv("./wm.csv")
wm_df_heritage <- read_csv("./wm_all.csv")
```

Late learners and native controls

Do they predict above chance?

The data analyzed using a linear model with intercept removed. This makes each parameter estimate a two-sided test of independence ($H_a \neq 0$). In order to make this test one-sided ($H_a > 0$) we will take the t-values from the model and calculate the associated probability from the t-distribution for a one-sided test using the model degrees of freedom. In R this can be done with the following function:

```
pt(t_values, mod_df, lower = FALSE)
```

The p-values from the model will now be one-sided tests that the mean difference is greater than 0. Next, we need to put the target fixations (dependent variable) on the same scale. As is, chance = 50%, thus everything will be significant because target fixations are on average at 50% as a minimum. To get around this issue we can subtract 0.5 from each participants mean target fixation at each landmark and test to see if that value is greater than 0. For example, if at the target word onset you are fixating on the target 50% of the time (i.e., at chance), then when we subtract 0.5 from 0.5, we get 0. 0 is not greater than 0 so it wouldn't be significant. We will conduct this test for each group, at each landmark. Then we will add the 0.5 back on to the model estimates and the confidence intervals for plotting purposes.

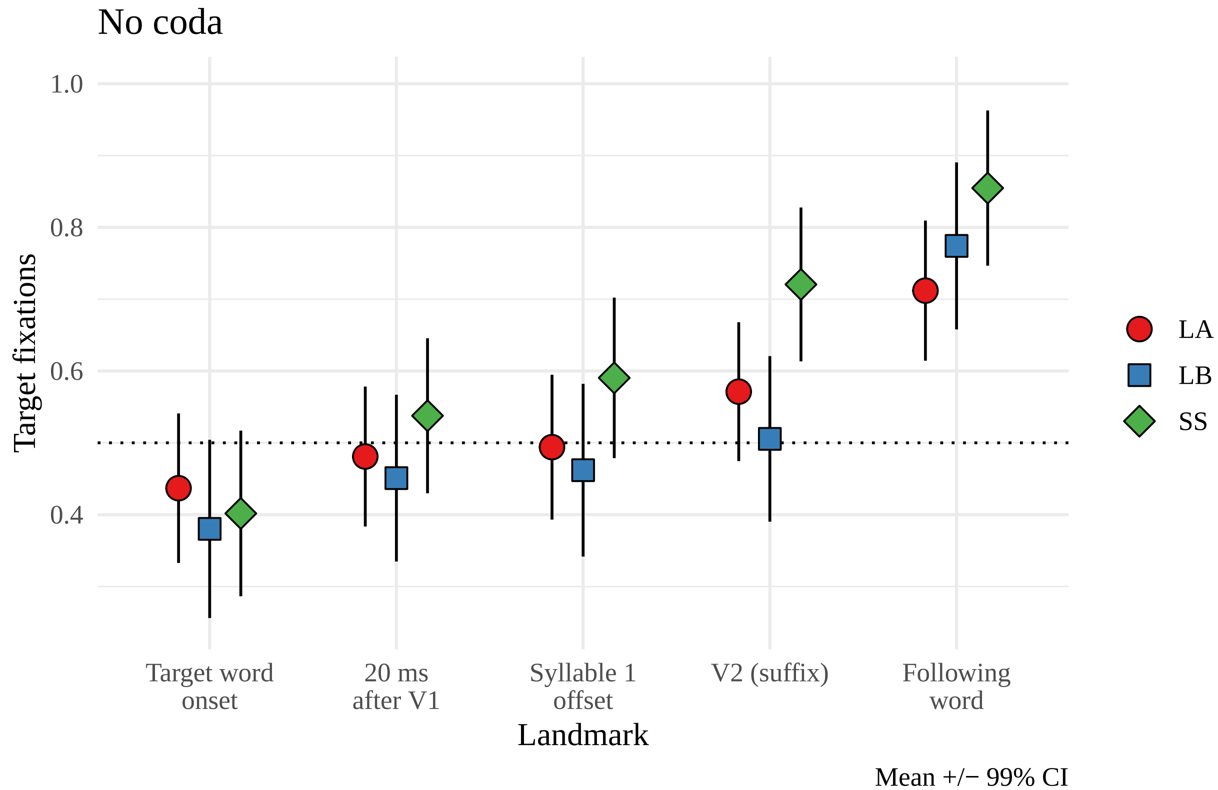
```
# Model degrees of freedom
learner_mod_df <- 65

learner_mods <- learners %>%
  filter(., !(landmark %in% c('start_sentence', 'word2_c1v1',
                              'end_sentence'))) %>%
  group_by(., participant, group, coda, landmark) %>%
  summarize(., target_fix = mean(targetProp)) %>%
  ungroup(.) %>%
  group_by(., landmark, coda) %>%
  do(tidy(lm(I(target_fix - 0.5) ~ -1 + group, data = .), conf.int = T,
          conf.level = 0.99)) %>%
  mutate(., p_adj = pt(statistic, learner_mod_df, lower = F),
            p_adj = formatC(p_adj, digits = 7, format = "f"),
            sig = if_else(p_adj < 0.05, true = "*", false = " ")) %>%
  ungroup(.) %>%
  mutate(., landmark = fct_relevel(landmark,
                                   'word3_c1v1', 'word3_20msafterv1',
                                   'word3_c2', 'word3_c3', 'word3_suffix')) %>%
  arrange(., coda, landmark)
```

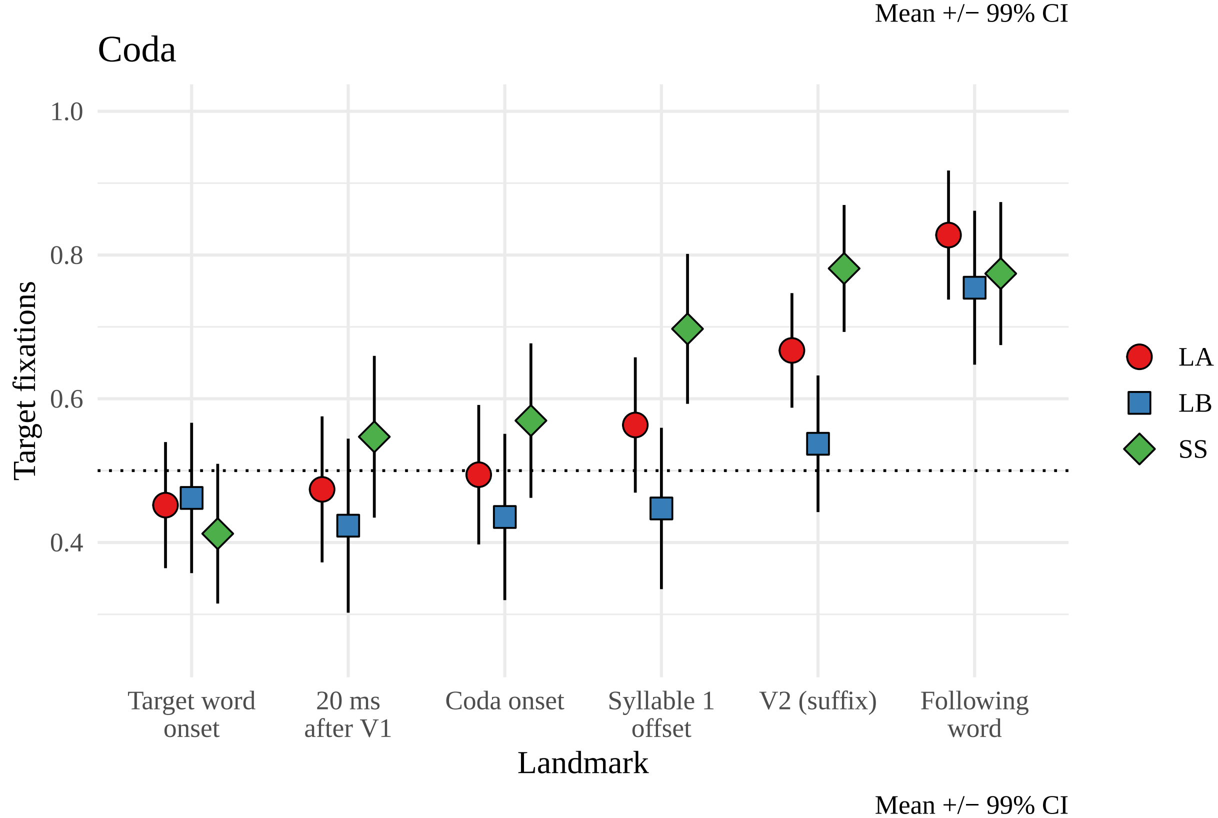
Table 1: Model output

landmark	term	estimate	std.error	statistic	conf.low	conf.high	p_adj	sig
No-coda targets								
	la	-0.06	0.04	-1.61	-0.17	0.04	0.9438315	
word3_c1v1	lb	-0.12	0.05	-2.56	-0.24	0.00	0.9936311	
	ss	-0.10	0.04	-2.26	-0.21	0.02	0.9864650	
	la	-0.02	0.04	-0.52	-0.12	0.08	0.6971842	
word3_20msafterv1	lb	-0.05	0.04	-1.12	-0.17	0.07	0.8671037	
	ss	0.04	0.04	0.93	-0.07	0.15	0.1787654	
	la	-0.01	0.04	-0.16	-0.11	0.09	0.5624449	
word3_c2	lb	-0.04	0.05	-0.84	-0.16	0.08	0.7982615	
	ss	0.09	0.04	2.15	-0.02	0.20	0.0176951	*
	la	0.07	0.04	1.96	-0.03	0.17	0.0274149	*
word3_suffix	lb	0.01	0.04	0.13	-0.11	0.12	0.4496902	
	ss	0.22	0.04	5.46	0.11	0.33	0.0000004	*
	la	0.21	0.04	5.76	0.11	0.31	0.0000001	*
word4_c1v1	lb	0.27	0.04	6.26	0.16	0.39	0.0000000	*
	ss	0.35	0.04	8.71	0.25	0.46	0.0000000	*
Coda targets								
	la	-0.05	0.03	-1.45	-0.14	0.04	0.9242526	
word3_c1v1	lb	-0.04	0.04	-0.96	-0.14	0.07	0.8308077	
	ss	-0.09	0.04	-2.40	-0.18	0.01	0.9902493	
	la	-0.03	0.04	-0.68	-0.13	0.08	0.7508646	
word3_20msafterv1	lb	-0.08	0.05	-1.68	-0.20	0.04	0.9510029	
	ss	0.05	0.04	1.11	-0.07	0.16	0.1353062	
	la	-0.01	0.04	-0.15	-0.10	0.09	0.5610294	
word3_c2	lb	-0.06	0.04	-1.48	-0.18	0.05	0.9281215	
	ss	0.07	0.04	1.72	-0.04	0.18	0.0452329	*
	la	0.06	0.04	1.79	-0.03	0.16	0.0390471	*
word3_c3	lb	-0.05	0.04	-1.24	-0.16	0.06	0.8910685	
	ss	0.20	0.04	5.02	0.09	0.30	0.0000022	*
	la	0.17	0.03	5.57	0.09	0.25	0.0000003	*
word3_suffix	lb	0.04	0.04	1.04	-0.06	0.13	0.1502988	
	ss	0.28	0.03	8.45	0.19	0.37	0.0000000	*
	la	0.33	0.03	9.68	0.24	0.42	0.0000000	*
word4_c1v1	lb	0.25	0.04	6.31	0.15	0.36	0.0000000	*
	ss	0.27	0.04	7.31	0.17	0.37	0.0000000	*

Note:
Parameter estimates show average target fixation minus 0.5.
P-values represent one-sided t-tests.
word3_c2 represents the 2nd syllable onset for no-coda targets and the coda onset for coda targets.

Landmark plots





Is working memory a factor?

```
## Joining, by = "participant"

## Data: learners_no_coda
## Models:
## learner_wm_nocoda_mod_null: cbind(targetCount, distractorCount) ~ 1 + (1 | participant)
## learner_wm_nocoda_mod_wm: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c
##                             Df    AIC    BIC  logLik deviance Chisq Chi Df
## learner_wm_nocoda_mod_null  2 7466.6 7475.5 -3731.3   7462.6
## learner_wm_nocoda_mod_wm    3 7468.3 7481.8 -3731.2   7462.3 0.265      1
##                             Pr(>Chisq)
## learner_wm_nocoda_mod_null
## learner_wm_nocoda_mod_wm       0.6067

## Data: learners_no_coda
## Models:
## learner_wm_nocoda_mod_null: cbind(targetCount, distractorCount) ~ 1 + (1 | participant)
## learner_wm_nocoda_mod_group: cbind(targetCount, distractorCount) ~ (1 | participant) + group
##                              Df    AIC    BIC  logLik deviance  Chisq
## learner_wm_nocoda_mod_null   2 7466.6 7475.5 -3731.3   7462.6
## learner_wm_nocoda_mod_group  4 7467.0 7484.9 -3729.5   7459.0 3.5964
##                              Chi Df Pr(>Chisq)
## learner_wm_nocoda_mod_null
## learner_wm_nocoda_mod_group      2     0.1656

## Data: learners_no_coda
## Models:
## learner_wm_nocoda_mod_add: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## learner_wm_nocoda_mod_add:     group
## learner_wm_nocoda_mod_full: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## learner_wm_nocoda_mod_full:     group + wm_c:group
##                             Df    AIC    BIC  logLik deviance  Chisq Chi Df
## learner_wm_nocoda_mod_add   5 7469.0 7491.4 -3729.5   7459.0
## learner_wm_nocoda_mod_full  7 7472.8 7504.2 -3729.4   7458.8 0.1418      2
##                             Pr(>Chisq)
## learner_wm_nocoda_mod_add
## learner_wm_nocoda_mod_full     0.9316

## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
##     group + wm_c:group
##    Data: learners_no_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC   logLik deviance df.resid
##   7472.8   7504.2  -3729.4   7458.8      649
##
## Scaled residuals:
##     Min      1Q  Median      3Q     Max
## -6.9889 -2.7701  0.5388  2.3060  6.8327
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
```

```
##  participant (Intercept) 1.573    1.254
## Number of obs: 656, groups:  participant, 50
##
## Fixed effects:
##               Estimate Std. Error z value Pr(>|z|)
## (Intercept)   0.963787   0.278255   3.464 0.000533 ***
## wm_c          0.003398   0.041580   0.082 0.934860
## groupla      -0.658286   0.423977  -1.553 0.120508
## grouplb      -0.630843   0.576098  -1.095 0.273505
## wm_c:groupla -0.011270   0.149609  -0.075 0.939950
## wm_c:grouplb  0.052991   0.146244   0.362 0.717095
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) wm_c   groupl groplb wm_c:gropl
## wm_c        -0.095
## groupla     -0.654  0.062
## grouplb     -0.481  0.046  0.315
## wm_c:groupl  0.026 -0.278  0.035 -0.013
## wm_c:groplb  0.027 -0.284 -0.018  0.558  0.079
```

```
## Data: learners_coda
## Models:
## learner_wm_coda_mod_null: cbind(targetCount, distractorCount) ~ 1 + (1 | participant)
## learner_wm_coda_mod_wm: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c
##                          Df   AIC   BIC  logLik deviance  Chisq Chi Df
## learner_wm_coda_mod_null  2 10125 10135 -5060.4    10121
## learner_wm_coda_mod_wm    3 10126 10140 -5060.0    10120 0.8807      1
##                          Pr(>Chisq)
## learner_wm_coda_mod_null
## learner_wm_coda_mod_wm        0.348
```

```
## Data: learners_coda
## Models:
## learner_wm_coda_mod_wm: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c
## learner_wm_coda_mod_group: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## learner_wm_coda_mod_group:     group
##                           Df   AIC   BIC  logLik deviance  Chisq Chi Df
## learner_wm_coda_mod_wm     3 10126 10140 -5060.0    10120
## learner_wm_coda_mod_group  5 10119 10144 -5054.6    10109 10.737      2
##                           Pr(>Chisq)
## learner_wm_coda_mod_wm
## learner_wm_coda_mod_group   0.004662 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Data: learners_coda
## Models:
## learner_wm_coda_mod_group: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## learner_wm_coda_mod_group:     group
## learner_wm_coda_mod_full: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## learner_wm_coda_mod_full:     group + wm_c:group
##                           Df   AIC   BIC  logLik deviance  Chisq Chi Df
## learner_wm_coda_mod_group  5 10119 10144 -5054.6    10109
```

```
## learner_wm_coda_mod_full   7 10123 10157 -5054.4    10109 0.4126      2
##                           Pr(>Chisq)
## learner_wm_coda_mod_group
## learner_wm_coda_mod_full      0.8136
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
##     group
##    Data: learners_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC   logLik deviance df.resid
##  10119.3  10143.5  -5054.6  10109.3      927
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -8.854 -2.832  1.130  2.170  4.799
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  participant (Intercept) 1.444    1.202
## Number of obs: 932, groups:  participant, 50
##
## Fixed effects:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.49806    0.26837   5.582 2.38e-08 ***
## wm_c         0.01146    0.03473   0.330 0.741537
## groupla     -0.83315    0.40607  -2.052 0.040194 *
## grouplb     -1.49604    0.45432  -3.293 0.000991 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##         (Intr) wm_c   groupl
## wm_c    -0.091
## groupla -0.662  0.073
## grouplb -0.608  0.242  0.405
```

There is no relationship between target fixations and working memory at the target word first syllable offsets (with or without coda). There are group effects (we already knew that though). Native controls focus on the target more than the learners. Here are some plots. It doesn't look like the groups are homogenious with regard to working memory, i.e., there are more green points on the left and more red points on the right (note: this analysis excluded participants to make the groups more homogenious). Bottom line: Natives and advanced learners have more target fixations at the offset of the first syllable of the target word if it has a coda. Without the coda, only natives fixate on the target at the offset of the first syllable. What's new? The native are already starting to predict at the onset of the coda as well. This isn't surprising given that they can also predict without the coda. Overall, the landmark analysis doesn't show us anything we don't already know.

Working memory plots

These are based on the model fits (i.e., not raw data). The plots from the raw data had confidence intervals that were so wide you couldn't really see anything.

Estimated target fixations +/− 99% CI.

Late vs. early learners and native controls

Do they predict above chance?

Same analysis as previously described.

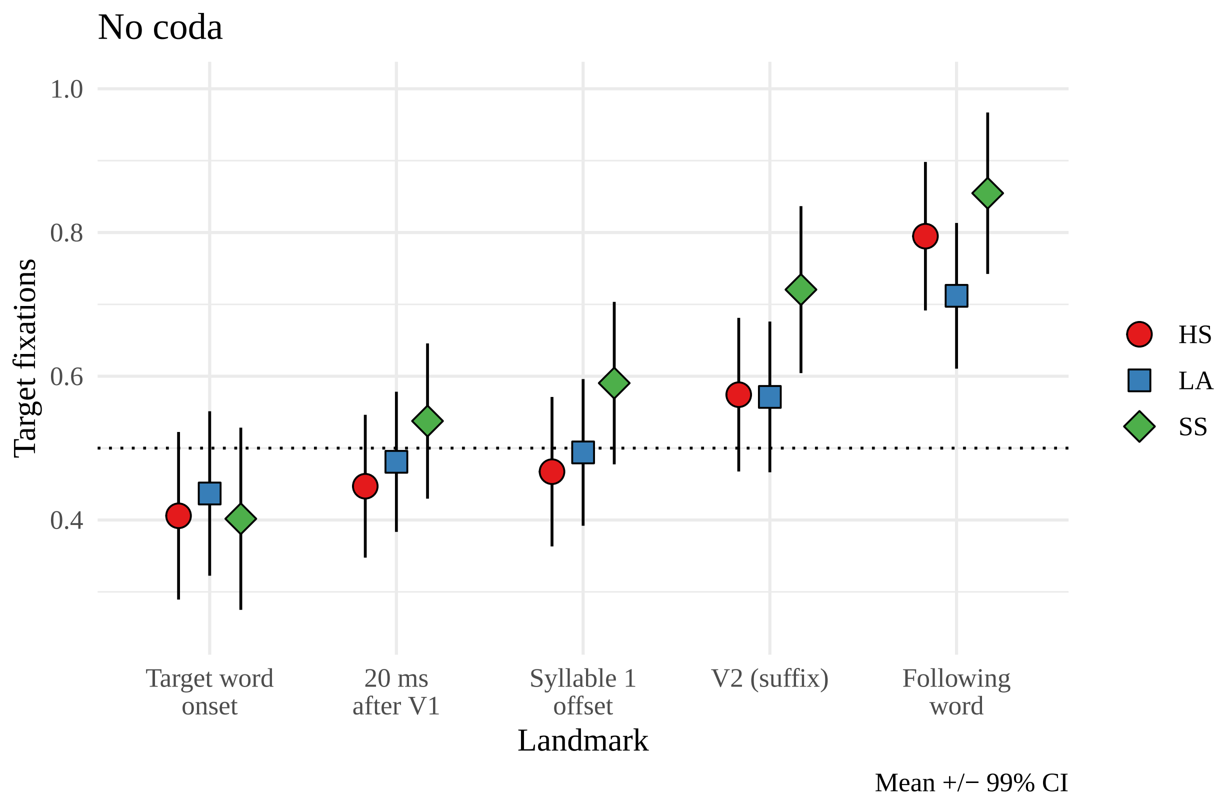
```
# Model degrees of freedom
heritage_mod_df <- 72

heritage_mods <- heritage %>%
  filter(., !(landmark %in% c('start_sentence', 'word2_c1v1',
                              'end_sentence'))) %>%
  group_by(., participant, group, coda, landmark) %>%
  summarize(., target_fix = mean(targetProp)) %>%
  ungroup(.) %>%
  group_by(., landmark, coda) %>%
  do(tidy(lm(I(target_fix - 0.5) ~ -1 + group, data = .), conf.int = T,
          conf.level = 0.99)) %>%
  mutate(., p_adj = pt(statistic, heritage_mod_df, lower = F),
            p_adj = formatC(p_adj, digits = 7, format = "f"),
            sig = if_else(p_adj < 0.05, true = "*", false = " ")) %>%
  ungroup(.) %>%
  mutate(., landmark = fct_relevel(landmark,
                                   'word3_c1v1', 'word3_20msafterv1',
                                   'word3_c2', 'word3_c3', 'word3_suffix')) %>%
  arrange(., coda, landmark)
```

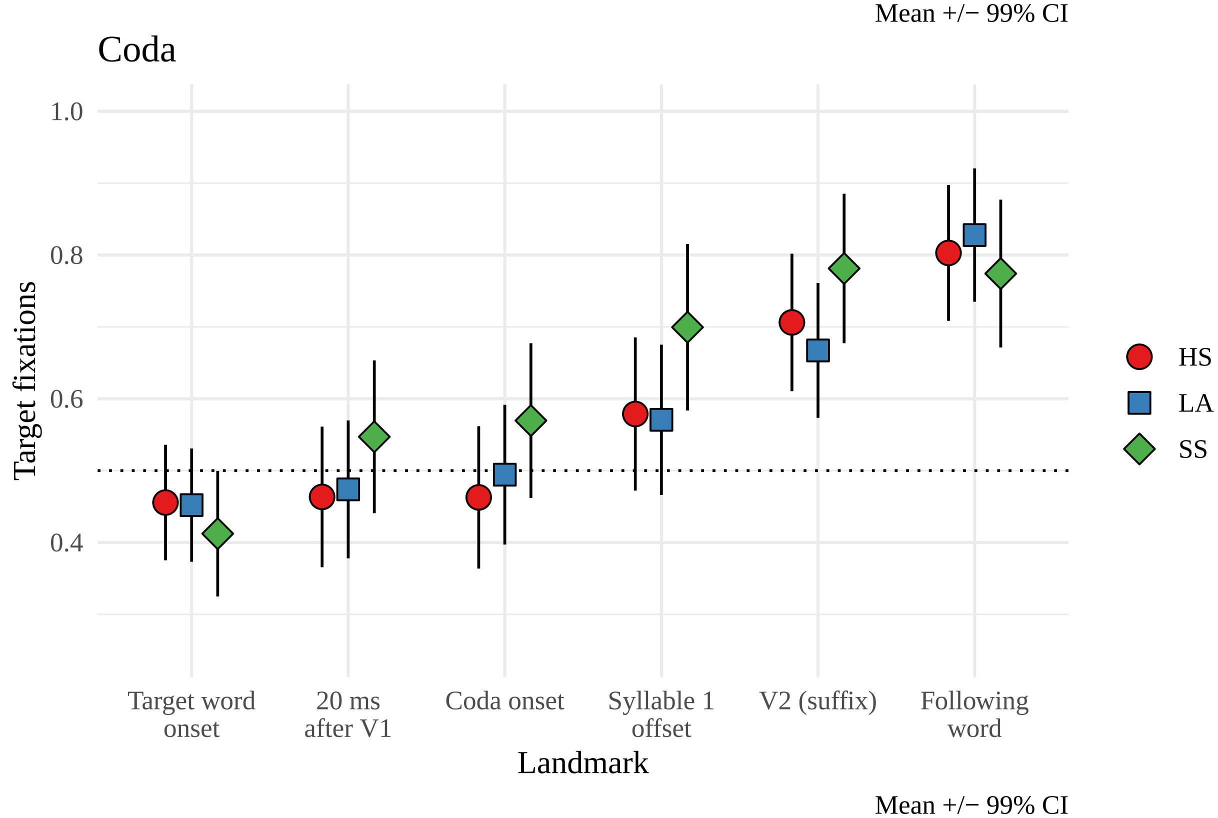
Table 2: Model output

landmark	term	estimate	std.error	statistic	conf.low	conf.high	p_adj	sig
No-coda targets								
	hs	-0.09	0.04	-2.14	-0.21	0.02	0.9819752	
word3_c1v1	la	-0.06	0.04	-1.46	-0.18	0.05	0.9257015	
	ss	-0.10	0.05	-2.05	-0.23	0.03	0.9780822	
	hs	-0.05	0.04	-1.41	-0.15	0.05	0.9188499	
word3_20msafterv1	la	-0.02	0.04	-0.52	-0.12	0.08	0.6965797	
	ss	0.04	0.04	0.92	-0.07	0.15	0.1795164	
	hs	-0.03	0.04	-0.83	-0.14	0.07	0.7965654	
word3_c2	la	-0.01	0.04	-0.16	-0.11	0.10	0.5615723	
	ss	0.09	0.04	2.12	-0.02	0.20	0.0188317	*
	hs	0.07	0.04	1.84	-0.03	0.18	0.0348610	*
word3_suffix	la	0.07	0.04	1.80	-0.03	0.18	0.0381995	*
	ss	0.22	0.04	5.02	0.10	0.34	0.0000018	*
	hs	0.29	0.04	7.55	0.19	0.40	0.0000000	*
word4_c1v1	la	0.21	0.04	5.53	0.11	0.31	0.0000002	*
	ss	0.35	0.04	8.36	0.24	0.47	0.0000000	*
Coda targets								
	hs	-0.04	0.03	-1.46	-0.12	0.04	0.9259936	
word3_c1v1	la	-0.05	0.03	-1.61	-0.13	0.03	0.9441519	
	ss	-0.09	0.03	-2.66	-0.18	0.00	0.9951562	
	hs	-0.04	0.04	-0.99	-0.13	0.06	0.8372537	
word3_20msafterv1	la	-0.03	0.04	-0.72	-0.12	0.07	0.7627565	
	ss	0.05	0.04	1.17	-0.06	0.15	0.1223290	
	hs	-0.04	0.04	-0.99	-0.14	0.06	0.8383116	
word3_c2	la	-0.01	0.04	-0.15	-0.10	0.09	0.5607754	
	ss	0.07	0.04	1.71	-0.04	0.18	0.0457271	*
	hs	0.08	0.04	1.96	-0.03	0.19	0.0271484	*
word3_c3	la	0.07	0.04	1.79	-0.03	0.18	0.0390024	*
	ss	0.20	0.04	4.56	0.08	0.32	0.0000104	*
	hs	0.21	0.04	5.71	0.11	0.30	0.0000001	*
word3_suffix	la	0.17	0.04	4.72	0.07	0.26	0.0000057	*
	ss	0.28	0.04	7.16	0.18	0.39	0.0000000	*
	hs	0.30	0.04	8.48	0.21	0.40	0.0000000	*
word4_c1v1	la	0.33	0.04	9.35	0.23	0.42	0.0000000	*
	ss	0.27	0.04	7.06	0.17	0.38	0.0000000	*

Note:
Parameter estimates show average target fixation minus 0.5.
P-values represent one-sided t-tests.
word3_c2 represents the 2nd syllable onset for no-coda targets and the coda onset for coda targets.

Landmark plots





Is working memory a factor?

```
## Joining, by = c("participant", "group")
```

```
## Warning: Column `group` joining character vector and factor, coercing into
## character vector
```

```
## Data: heritage_no_coda
## Models:
## heritage_wm_nocoda_mod_null: cbind(targetCount, distractorCount) ~ 1 + (1 | participant)
## heritage_wm_nocoda_mod_wm: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c
##                             Df    AIC    BIC  logLik deviance  Chisq
## heritage_wm_nocoda_mod_null  2 4888.6 4896.7 -2442.3   4884.6
## heritage_wm_nocoda_mod_wm    3 4889.2 4901.4 -2441.6   4883.2 1.4366
##                             Chi Df Pr(>Chisq)
## heritage_wm_nocoda_mod_null
## heritage_wm_nocoda_mod_wm        1     0.2307
```

```
## Data: heritage_no_coda
## Models:
## heritage_wm_nocoda_mod_null: cbind(targetCount, distractorCount) ~ 1 + (1 | participant)
## heritage_wm_nocoda_mod_group: cbind(targetCount, distractorCount) ~ (1 | participant) + group
##                              Df    AIC    BIC  logLik deviance  Chisq
## heritage_wm_nocoda_mod_null   2 4888.6 4896.7 -2442.3   4884.6
## heritage_wm_nocoda_mod_group  4 4880.7 4896.9 -2436.3   4872.7 11.932
##                              Chi Df Pr(>Chisq)
## heritage_wm_nocoda_mod_null
## heritage_wm_nocoda_mod_group      2   0.002564 **
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Data: heritage_no_coda
## Models:
## heritage_wm_nocoda_mod_add: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## heritage_wm_nocoda_mod_add:     group
## heritage_wm_nocoda_mod_full: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## heritage_wm_nocoda_mod_full:     group + wm_c:group
##                             Df    AIC    BIC  logLik deviance  Chisq
## heritage_wm_nocoda_mod_add   5 4881.0 4901.3 -2435.5   4871.0
## heritage_wm_nocoda_mod_full  7 4883.3 4911.7 -2434.6   4869.3 1.7452
##                             Chi Df Pr(>Chisq)
## heritage_wm_nocoda_mod_add
## heritage_wm_nocoda_mod_full      2     0.4179
```

```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
##     group + wm_c:group
##    Data: heritage_no_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC   logLik deviance df.resid
##   4883.3   4911.7  -2434.6   4869.3      423
##
## Scaled residuals:
```

```
##    Min     1Q Median     3Q    Max 
## -6.929 -2.757  0.000  2.353  6.397 
## 
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  participant (Intercept) 0.788    0.8877  
## Number of obs: 430, groups:  participant, 67
## 
## Fixed effects:
##               Estimate Std. Error z value Pr(>|z|)    
## (Intercept)   0.976580   0.221661   4.406 1.05e-05 ***
## wm_c          0.009685   0.115790   0.084 0.933338    
## grouphs      -1.001574   0.302475  -3.311 0.000929 ***
## groupla      -0.892305   0.287455  -3.104 0.001908 ** 
## wm_c:grouphs -0.154344   0.139970  -1.103 0.270159    
## wm_c:groupla -0.026759   0.145441  -0.184 0.854024    
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## Correlation of Fixed Effects:
##             (Intr) wm_c   grophs groupl wm_c:grph
## wm_c         0.059                               
## grouphs     -0.733 -0.043                        
## groupla     -0.771 -0.045  0.565                 
## wm_c:grophs -0.052 -0.829  0.041  0.040          
## wm_c:groupl -0.047 -0.796  0.034  0.059  0.660
```

```
## Data: heritage_coda
## Models:
## heritage_wm_coda_mod_null: cbind(targetCount, distractorCount) ~ 1 + (1 | participant)
## heritage_wm_coda_mod_wm: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c
##                           Df    AIC    BIC  logLik deviance  Chisq Chi Df
## heritage_wm_coda_mod_null  2 6613.9 6622.8 -3304.9   6609.9              
## heritage_wm_coda_mod_wm    3 6615.4 6628.7 -3304.7   6609.4 0.4882      1
##                           Pr(>Chisq)
## heritage_wm_coda_mod_null           
## heritage_wm_coda_mod_wm       0.4847
```

```
## Data: heritage_coda
## Models:
## heritage_wm_coda_mod_wm: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c
## heritage_wm_coda_mod_group: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c + 
## heritage_wm_coda_mod_group:     group
##                            Df    AIC    BIC  logLik deviance  Chisq Chi Df
## heritage_wm_coda_mod_wm     3 6615.4 6628.7 -3304.7   6609.4              
## heritage_wm_coda_mod_group  5 6611.6 6633.7 -3300.8   6601.6 7.8381      2
##                            Pr(>Chisq)  
## heritage_wm_coda_mod_wm                
## heritage_wm_coda_mod_group    0.01986 *
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
## Data: heritage_coda
## Models:
## heritage_wm_coda_mod_add: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
```

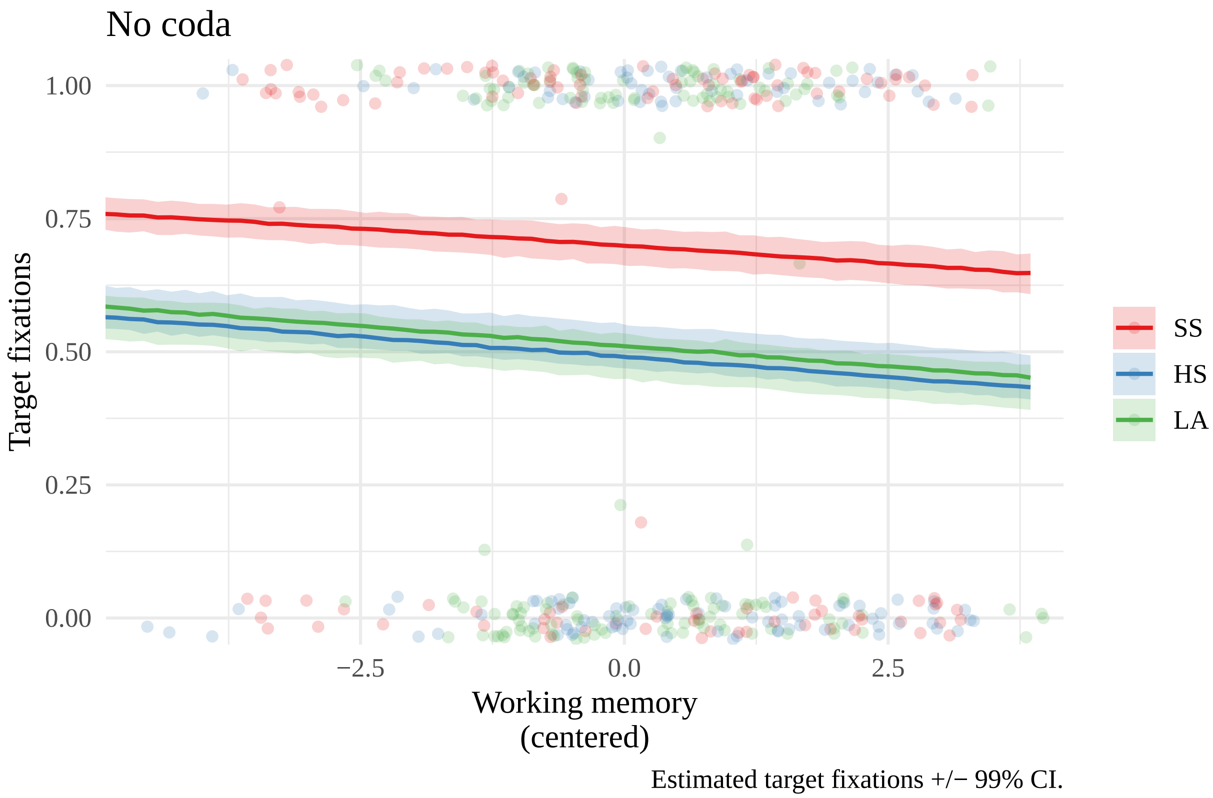
```
## heritage_wm_coda_mod_add:     group
## heritage_wm_coda_mod_full: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
## heritage_wm_coda_mod_full:     group + wm_c:group
##                           Df    AIC    BIC  logLik deviance  Chisq Chi Df
## heritage_wm_coda_mod_add   5 6611.6 6633.7 -3300.8   6601.6
## heritage_wm_coda_mod_full  7 6613.0 6644.0 -3299.5   6599.0 2.6037      2
##                           Pr(>Chisq)
## heritage_wm_coda_mod_add
## heritage_wm_coda_mod_full      0.272
```

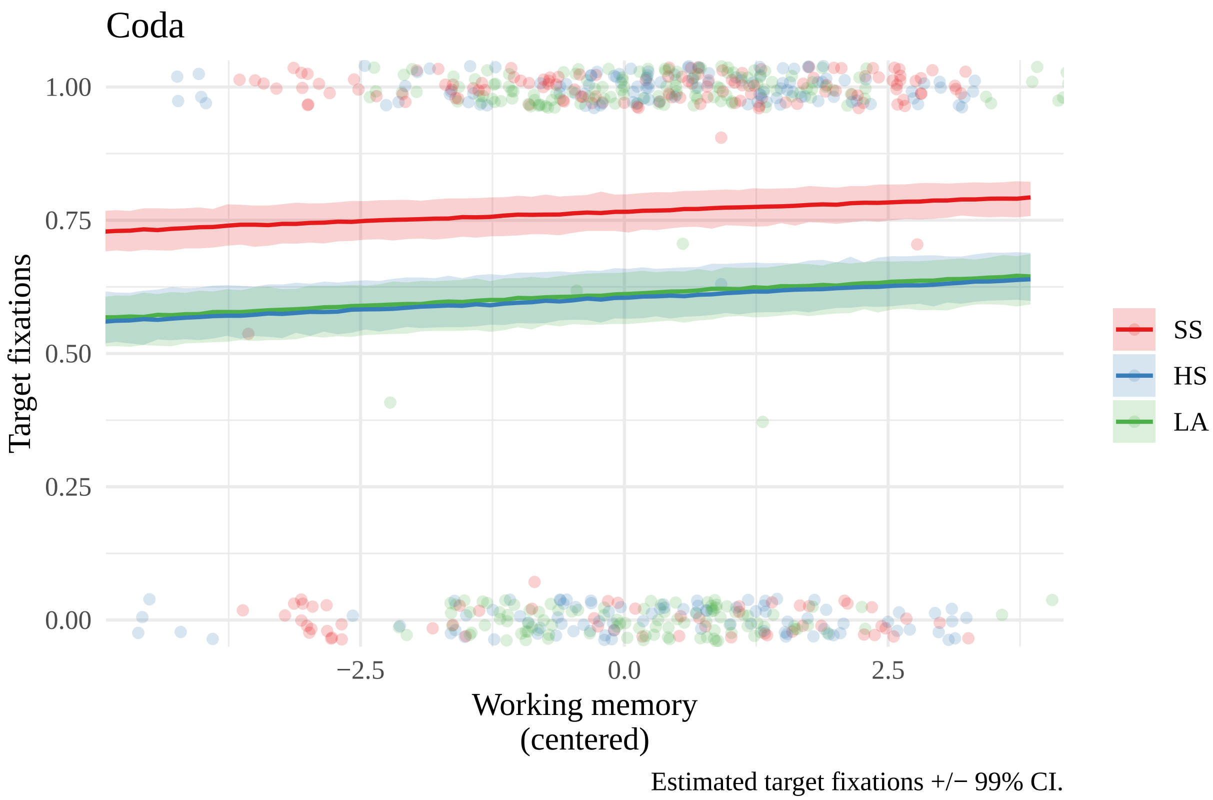
```
## Generalized linear mixed model fit by maximum likelihood (Laplace
##   Approximation) [glmerMod]
##  Family: binomial  ( logit )
## Formula: cbind(targetCount, distractorCount) ~ (1 | participant) + wm_c +
##     group + wm_c:group
##    Data: learners_coda
## Control: glmerControl(optimizer = "bobyqa")
##
##      AIC      BIC   logLik deviance df.resid
##  10122.9  10156.7  -5054.4  10108.9      925
##
## Scaled residuals:
##    Min     1Q Median     3Q    Max
## -8.855 -2.831  1.130  2.178  4.800
##
## Random effects:
##  Groups      Name        Variance Std.Dev.
##  participant (Intercept) 1.424    1.193
## Number of obs: 932, groups:  participant, 50
##
## Fixed effects:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  1.49327    0.26689   5.595  2.2e-08 ***
## wm_c          0.01539    0.03728   0.413  0.67972
## groupla      -0.84142    0.40378  -2.084  0.03718 *
## grouplb      -1.42174    0.54729  -2.598  0.00938 **
## wm_c:groupla -0.08645    0.14252  -0.607  0.54416
## wm_c:grouplb  0.02431    0.13802   0.176  0.86018
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Correlation of Fixed Effects:
##             (Intr) wm_c   groupl groplb wm_c:gropl
## wm_c        -0.101
## groupla     -0.660  0.066
## grouplb     -0.488  0.049  0.322
## wm_c:groupl  0.026 -0.262  0.034 -0.013
## wm_c:groplb  0.027 -0.270 -0.018  0.562  0.071
```

Almost exactly the same as above. No effect of working memory on target fixations as a function of group (in either coda or no-coda targets).

Working memory plots

Same as before. These are based on the model fits (i.e., not raw data). The plots from the raw data had confidence intervals that were so wide you couldn't really see anything.




Coda
1.00
0.75
0.50
0.25
0.00
Target fixations
−2.5
0.0
2.5
Working memory
(centered)
SS
HS
LA
Estimated target fixations +/− 99% CI.