

Repeated Lexical Retrieval: Experiment 2

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1 Reading File

```
> PrimeRetrieval <- read.csv("E3_YA_Responses.csv",
+                             header = TRUE, sep = ",")
> library(dplyr)
> PrimeRetrieval = PrimeRetrieval %>% filter(AgeGroup == "Young")
```

2 LME

```
> library(lme4)
> contrasts(PrimeRetrieval$PrimeCondition)= contr.treatment(4, base = 4)
> prime_lmer2 = glmer(data = PrimeRetrieval,
+                     Accuracy ~ PrimeCondition +
+                     (1|Subject) + (1|Stimuli2),
+                     family = "binomial",
+                     control=glmerControl(optimizer="bobyqa",
+                     optCtrl=list(maxfun=100000)))
> summary(prime_lmer2)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial (logit)
Formula: Accuracy ~ PrimeCondition + (1 | Subject) + (1 | Stimuli2)
Data: PrimeRetrieval
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))
```

AIC	BIC	logLik	deviance	df.resid
3634.6	3671.5	-1811.3	3622.6	3450

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.1337	-0.5810	-0.3166	0.6242	6.6789

Random effects:

Groups	Name	Variance	Std.Dev.
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```

Stimuli2 (Intercept) 1.8714    1.3680
Subject   (Intercept) 0.5131    0.7163
Number of obs: 3456, groups:  Stimuli2, 72; Subject, 48

Fixed effects:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.77392    0.21007  -3.684  0.00023 ***
PrimeCondition1 -0.25640    0.11965  -2.143  0.03212 *
PrimeCondition2 -0.07342    0.11869  -0.619  0.53616
PrimeCondition3 -0.15953    0.11951  -1.335  0.18192
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
              (Intr) PrmCn1 PrmCn2
PrimeCndtn1  -0.278
PrimeCndtn2  -0.281  0.495
PrimeCndtn3  -0.278  0.491  0.497

```

```

>
> # confint(prime_lmer2)
> #
> # > confint(prime_lmer2)
> # Computing profile confidence intervals ...
> #                2.5 %          97.5 %
> # .sig01           1.1418314    1.66248456
> # .sig02           0.5641225    0.92149953
> # (Intercept)     -1.1916777   -0.36114974
> # PrimeCondition1 -0.4950192   -0.01945911
> # PrimeCondition2 -0.3090286    0.16187213
> # PrimeCondition3 -0.3970849    0.07727542

```

3 Prime And Target Accuracy

```

> library(dplyr)
> agg_condition <- group_by(PrimeRetrieval, PrimeCondition)%>%
+   summarise_at(vars(Accuracy), mean)
> agg_sub_condition <- group_by(PrimeRetrieval, Subject, PrimeCondition)%>%
+   summarise_at(vars(Accuracy), mean)
> agg_sub_condition$Subject <- as.factor(agg_sub_condition$Subject)
> agg_sub_condition$PrimeCondition <- as.factor(agg_sub_condition$PrimeCondition)
> agg_sub_prime = group_by(PrimeRetrieval, Subject, PrimeCondition) %>%
+   summarise_at(vars(PrimeFirstResp_ACC), mean)
> ## target accuracy anova
>
> prime_aov = aov(data = agg_sub_condition, Accuracy ~ PrimeCondition +

```

```
+ Error(Subject/PrimeCondition))
> summary(prime_aov)
```

```
Error: Subject
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals 47  2.865  0.06097

Error: Subject:PrimeCondition
      Df Sum Sq Mean Sq F value Pr(>F)
PrimeCondition  3  0.0485  0.01616  1.058  0.369
Residuals    141  2.1537  0.01527
```

```
> ## prime accuracy anova
> agg_sub_prime$Subject = as.factor(agg_sub_prime$Subject)
> primeaccuracy_aov = aov(data = agg_sub_prime,
+                           PrimeFirstResp_ACC ~ PrimeCondition +
+                           Error(Subject/PrimeCondition))
> summary(primeaccuracy_aov)
```

```
Error: Subject
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals 47  2.068  0.04401

Error: Subject:PrimeCondition
      Df Sum Sq Mean Sq F value    Pr(>F)
PrimeCondition  3  0.6128  0.20426  15.53 8.81e-09 ***
Residuals    141  1.8548  0.01315
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> ## specific t-tests
> prime_p = agg_sub_prime %>% filter(PrimeCondition == "P")
> prime_r = agg_sub_prime %>% filter(PrimeCondition == "R")
> prime_b = agg_sub_prime %>% filter(PrimeCondition == "B")
> prime_u = agg_sub_prime %>% filter(PrimeCondition == "U")
> t.test(prime_p$PrimeFirstResp_ACC, prime_r$PrimeFirstResp_ACC, paired = TRUE)
```

```
Paired t-test

data: prime_p$PrimeFirstResp_ACC and prime_r$PrimeFirstResp_ACC
t = 4.9091, df = 47, p-value = 1.143e-05
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.0689931 0.1648032
sample estimates:
mean of the differences
 0.1168981
```

```
> t.test(prime_p$PrimeFirstResp_ACC, prime_b$PrimeFirstResp_ACC, paired = TRUE)
```

Paired t-test

```
data: prime_p$PrimeFirstResp_ACC and prime_b$PrimeFirstResp_ACC
t = 6.5065, df = 47, p-value = 4.589e-08
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.1055408 0.2000148
sample estimates:
mean of the differences
      0.1527778
```

```
> t.test(prime_p$PrimeFirstResp_ACC, prime_u$PrimeFirstResp_ACC, paired = TRUE)
```

Paired t-test

```
data: prime_p$PrimeFirstResp_ACC and prime_u$PrimeFirstResp_ACC
t = 4.0477, df = 47, p-value = 0.0001917
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.04599164 0.13687873
sample estimates:
mean of the differences
      0.09143519
```

```
> t.test(prime_b$PrimeFirstResp_ACC, prime_r$PrimeFirstResp_ACC, paired = TRUE)
```

Paired t-test

```
data: prime_b$PrimeFirstResp_ACC and prime_r$PrimeFirstResp_ACC
t = -1.83, df = 47, p-value = 0.07359
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.075322360 0.003563101
sample estimates:
mean of the differences
     -0.03587963
```

```
> t.test(prime_b$PrimeFirstResp_ACC, prime_u$PrimeFirstResp_ACC, paired = TRUE)
```

Paired t-test

```
data: prime_b$PrimeFirstResp_ACC and prime_u$PrimeFirstResp_ACC
t = -2.3122, df = 47, p-value = 0.0252
alternative hypothesis: true difference in means is not equal to 0
```

```

95 percent confidence interval:
-0.114714633 -0.007970552
sample estimates:
mean of the differences
-0.06134259

```

```
> t.test(prime_r$PrimeFirstResp_ACC, prime_u$PrimeFirstResp_ACC, paired = TRUE)
```

Paired t-test

```

data: prime_r$PrimeFirstResp_ACC and prime_u$PrimeFirstResp_ACC
t = -1.0649, df = 47, p-value = 0.2924
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
-0.07356625 0.02264032
sample estimates:
mean of the differences
-0.02546296

```

```

> ## accounting for mean participant accuracy on the prime?
>
> participant_acc = group_by(PrimeRetrieval, Subject) %>%
+   summarise_at(vars(Accuracy, PrimeFirstResp_ACC), mean)
> participant_acc$MeanAcc = (participant_acc$Accuracy +
+   participant_acc$PrimeFirstResp_ACC)/2
> median_acc = median(participant_acc$MeanAcc)
> colnames(participant_acc) = c("Subject", "TargetAcc", "PrimeAcc", "MeanAcc")
> ## accounting for mean prime accuracy
>
> item_acc = group_by(PrimeRetrieval, Stimuli2, PrimeCondition) %>%
+   summarise_at(vars(PrimeFirstResp_ACC), mean)
> colnames(item_acc) = c("Stimuli2", "PrimeCondition", "PrimeAcc")
> PrimeRetrieval = merge(PrimeRetrieval, item_acc,
+   by = c("Stimuli2", "PrimeCondition"))
> PrimeRetrieval2 = merge(PrimeRetrieval, participant_acc[,c(1,3,4)],
+   by = c("Subject"))

```

3.1 Using lmer

```

> # since finaldata has several missing trials -- need 704 have 662, ANOVA is probably
>
> contrasts(PrimeRetrieval$PrimeCondition) = contr.treatment(4, base = 4)
> PrimeRetrieval$PrimeFirstResp_ACC = as.factor(PrimeRetrieval$PrimeFirstResp_ACC)
> m_young_prime = glmer(data = PrimeRetrieval, Accuracy ~
+   PrimeFirstResp_ACC*PrimeCondition + PrimeAcc +
+   (1|Subject) + (1|Stimuli2),
+   family = "binomial",

```

```
+ control=glmerControl(optimizer="bobyqa",
+ optCtrl=list(maxfun=100000)))
> summary(m_young_prime)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial ( logit )
Formula: Accuracy ~ PrimeFirstResp_ACC * PrimeCondition + PrimeAcc + (1 |
Subject) + (1 | Stimuli2)
Data: PrimeRetrieval
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))
```

AIC	BIC	logLik	deviance	df.resid
3624.6	3692.2	-1801.3	3602.6	3445

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.0435	-0.5758	-0.3106	0.6261	5.3680

Random effects:

Groups	Name	Variance	Std.Dev.
Stimuli2	(Intercept)	1.803	1.3428
Subject	(Intercept)	0.473	0.6877

Number of obs: 3456, groups: Stimuli2, 72; Subject, 48

Fixed effects:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.74421	0.23661	-3.145	0.00166 **
PrimeFirstResp_ACC1	0.05991	0.17359	0.345	0.72999
PrimeCondition1	-0.54380	0.17284	-3.146	0.00165 **
PrimeCondition2	-0.08893	0.17923	-0.496	0.61978
PrimeCondition3	-0.41195	0.17348	-2.375	0.01757 *
PrimeAcc	-0.10312	0.20631	-0.500	0.61719
PrimeFirstResp_ACC1:PrimeCondition1	0.60408	0.25594	2.360	0.01826 *
PrimeFirstResp_ACC1:PrimeCondition2	0.03717	0.25465	0.146	0.88394
PrimeFirstResp_ACC1:PrimeCondition3	0.50539	0.25337	1.995	0.04608 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	PrFR_ACC1	PrmCn1	PrmCn2	PrmCn3	PrmAcc	PFR_ACC1:PC1
PrmFrR_ACC1	-0.288						
PrimeCndtn1	-0.387	0.451					
PrimeCndtn2	-0.346	0.447	0.457				
PrimeCndtn3	-0.372	0.449	0.473	0.448			
PrimeAcc	-0.354	-0.154	0.141	0.060	0.111		
PFR_ACC1:PC1	0.300	-0.640	-0.719	-0.329	-0.341	-0.175	
PFR_ACC1:PC2	0.305	-0.640	-0.356	-0.744	-0.342	-0.193	0.501

```

PFR_ACC1:PC3  0.296 -0.640      -0.349 -0.322 -0.722 -0.168  0.492
              PFR_ACC1:PC2
PrmFrR_ACC1
PrimeCndtn1
PrimeCndtn2
PrimeCndtn3
PrimeAcc
PFR_ACC1:PC1
PFR_ACC1:PC2
PFR_ACC1:PC3  0.493

```

```

> options(contrasts = c("contr.sum","contr.poly"))
> car::Anova(m_young_prime)

```

Analysis of Deviance Table (Type II Wald chisquare tests)

Response: Accuracy

	Chisq	Df	Pr(>Chisq)
PrimeFirstResp_ACC	8.4535	1	0.003643 **
PrimeCondition	4.6254	3	0.201370
PrimeAcc	0.2498	1	0.617186
PrimeFirstResp_ACC:PrimeCondition	9.0422	3	0.028735 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

> anova(m_young_prime)

```

Analysis of Variance Table

	Df	Sum Sq	Mean Sq	F value
PrimeFirstResp_ACC	1	11.5732	11.5732	11.5732
PrimeCondition	3	4.6078	1.5359	1.5359
PrimeAcc	1	0.0264	0.0264	0.0264
PrimeFirstResp_ACC:PrimeCondition	3	9.1290	3.0430	3.0430

```

> # > confint(m_young_prime) unrelated and primeret0 as baseline
> # Computing profile confidence intervals ...
> #
> #           2.5 %           97.5 %
> # .sig01           1.1189433    1.633996424
> # .sig02           0.5387244    0.888068921
> # (Intercept)     -1.1652470   -0.267459539
> # PrimeFirstResp_ACC1 -0.2023619    0.142159609
> # PrimeCondition1    -0.4804850   -0.004245685
> # PrimeCondition2    -0.3087080    0.167440999
> # PrimeCondition3    -0.3977035    0.078274447
> # PrimeAcc          -0.5127288    0.311643685
> # PrimeFirstResp_ACC1:PrimeCondition1 -0.5565369   -0.048968479
> # PrimeFirstResp_ACC1:PrimeCondition2 -0.2714417    0.233790347

```

```
> # PrimeFirstResp_ACC1:PrimeCondition3 -0.5042746 -0.002000942
>
> m_young_prime2 = lme4::glmer(data = PrimeRetrieval, Accuracy ~
+                               PrimeFirstResp_ACC*PrimeCondition +
+                               (1|Subject) + (1|Stimuli2),
+                               family = "binomial",
+                               control=glmerControl(optimizer="bobyqa",
+                               optCtrl=list(maxfun=100000)))
> summary(m_young_prime2)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial (logit )
Formula: Accuracy ~ PrimeFirstResp_ACC * PrimeCondition + (1 | Subject) +
(1 | Stimuli2)
Data: PrimeRetrieval
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))
```

AIC	BIC	logLik	deviance	df.resid
3622.9	3684.3	-1801.4	3602.9	3446

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.0687	-0.5779	-0.3095	0.6294	5.4175

Random effects:

Groups	Name	Variance	Std.Dev.
Stimuli2	(Intercept)	1.7910	1.338
Subject	(Intercept)	0.4761	0.690

Number of obs: 3456, groups: Stimuli2, 72; Subject, 48

Fixed effects:

	Estimate	Std. Error	z value	Pr(> z)	
(Intercept)	-0.76268	0.20531	-3.715	0.000203	***
PrimeFirstResp_ACC1	-0.02328	0.08568	-0.272	0.785888	
PrimeCondition1	-0.24100	0.12007	-2.007	0.044725	*
PrimeCondition2	-0.07732	0.11904	-0.650	0.515991	
PrimeCondition3	-0.16052	0.12000	-1.338	0.180994	
PrimeFirstResp_ACC1:PrimeCondition1	-0.29089	0.12590	-2.310	0.020863	*
PrimeFirstResp_ACC1:PrimeCondition2	-0.00619	0.12485	-0.050	0.960454	
PrimeFirstResp_ACC1:PrimeCondition3	-0.24211	0.12485	-1.939	0.052481	.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	PrFR_ACC1	PrmCn1	PrmCn2	PrmCn3	PFR_ACC1:PC1	PFR_ACC1:PC2
PrmFrR_ACC1	-0.018						
PrimeCndtn1	-0.279	0.031					


```

PrimeCndtn2  -0.284  0.030      0.486
PrimeCndtn3  -0.280  0.031      0.482  0.487
PFR_ACC1:PC1   0.008 -0.686     -0.034 -0.020 -0.024
PFR_ACC1:PC2   0.011 -0.691     -0.025  0.073 -0.023  0.483
PFR_ACC1:PC3   0.009 -0.684     -0.026 -0.023 -0.009  0.476      0.475

```

```
> car::Anova(m_young_prime2)
```

Analysis of Deviance Table (Type II Wald chisquare tests)

Response: Accuracy

	Chisq	Df	Pr(>Chisq)
PrimeFirstResp_ACC	11.2801	1	0.0007834 ***
PrimeCondition	4.6235	3	0.2015394
PrimeFirstResp_ACC:PrimeCondition	8.8303	3	0.0316346 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> anova(m_young_prime, m_young_prime2) ## prime acc not needed
```

Data: PrimeRetrieval

Models:

```
m_young_prime2: Accuracy ~ PrimeFirstResp_ACC * PrimeCondition + (1 | Subject) +
```

```
m_young_prime2: (1 | Stimuli2)
```

```
m_young_prime: Accuracy ~ PrimeFirstResp_ACC * PrimeCondition + PrimeAcc + (1 |
```

```
m_young_prime: Subject) + (1 | Stimuli2)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
m_young_prime2	10	3622.9	3684.3	-1801.4	3602.9				
m_young_prime	11	3624.6	3692.2	-1801.3	3602.6	0.2443		1	0.6211

Figures: Mean Accuracy

Retrieval by Primes

```

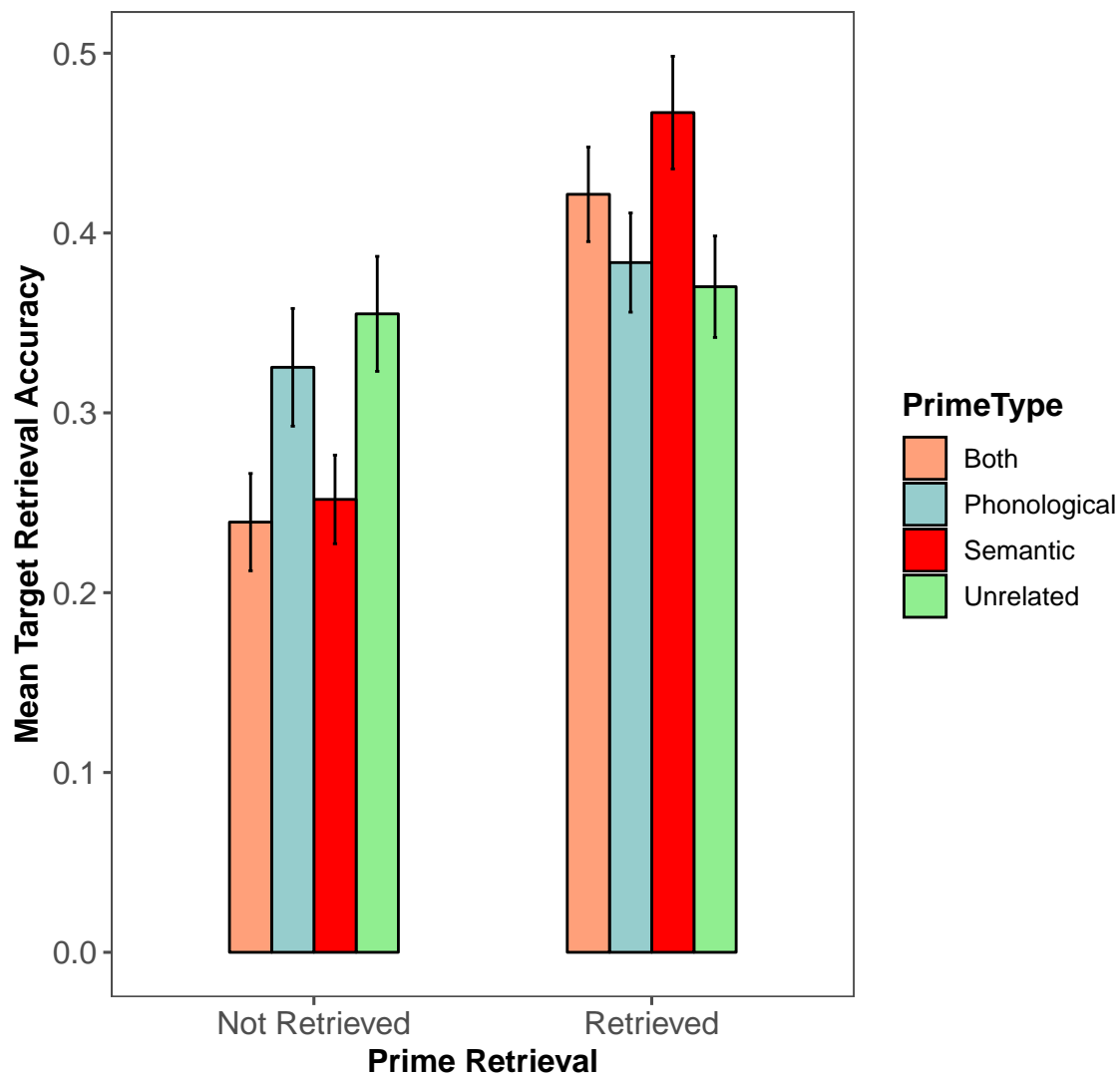
> agg_sub_condition_retrieval = group_by(PrimeRetrieval, Subject,
+                                         PrimeCondition, PrimeFirstResp_ACC) %>%
+                                         summarise_at(vars(Accuracy), mean)
> agg_acc_retrieval = Rmisc::summarySE(agg_sub_condition_retrieval,
+                                       measurevar = "Accuracy",
+                                       groupvars = c("PrimeCondition", "PrimeFirstResp_ACC"))
> library(ggplot2)
> library(ggthemes)
> agg_acc_retrieval %>% mutate(PrimeType = factor(PrimeCondition,
+                                                  levels = unique(PrimeCondition),
+                                                  labels = c("Both", "Phonological",
+                                                  "Semantic", "Unrelated")),
+                             `Prime Retrieval` = factor(PrimeFirstResp_ACC,

```

```

+           levels = unique(PrimeFirstResp_ACC),
+           labels = c("Not Retrieved", "Retrieved")))%>%
+   ggplot(aes(x = `Prime Retrieval`, y = Accuracy,
+             fill = PrimeType)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.5, color = "black")+
+   geom_errorbar(aes(ymin = Accuracy - se, ymax = Accuracy + se),
+                 width=.05, position=position_dodge(.5)) +
+   theme_few()+
+   xlab("Prime Retrieval") + ylab("Mean Target Retrieval Accuracy") +
+   ggtitle("") +
+   scale_fill_manual(values = c( "lightsalmon",
+                                "paleturquoise3","red","lightgreen"))+
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
>

```



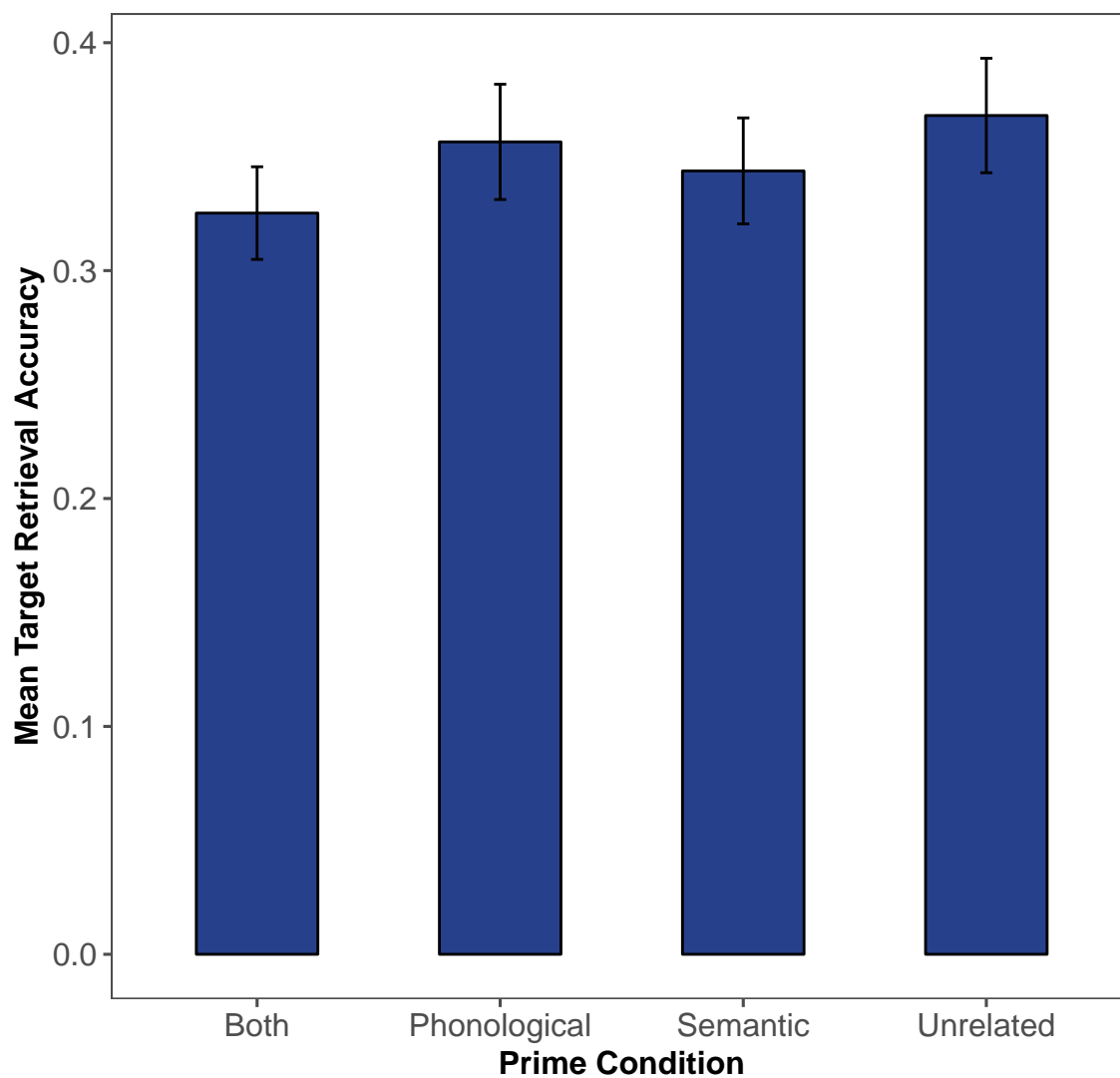
Target

```
> agg_acc = Rmisc::summarySE(agg_sub_condition,
+                             measurevar = "Accuracy",
+                             groupvars = c("PrimeCondition"))
> library(ggplot2)
> library(ggthemes)
> agg_acc %>% mutate(PrimeType = factor(PrimeCondition,
+                                       levels = unique(PrimeCondition),
+                                       labels = c("Both", "Phonological",
+                                                  "Semantic", "Unrelated")))%>%
```

```

+   ggplot(aes(x = PrimeType, y = Accuracy)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.5,
+           fill = "royalblue4", color = "black")+
+   geom_errorbar(aes(ymin = Accuracy - se, ymax = Accuracy + se),
+               width=.05, position=position_dodge(.5)) +
+   theme_few()+
+   xlab("Prime Condition") + ylab("Mean Target Retrieval Accuracy") +
+   ggtitle("") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
+
>

```



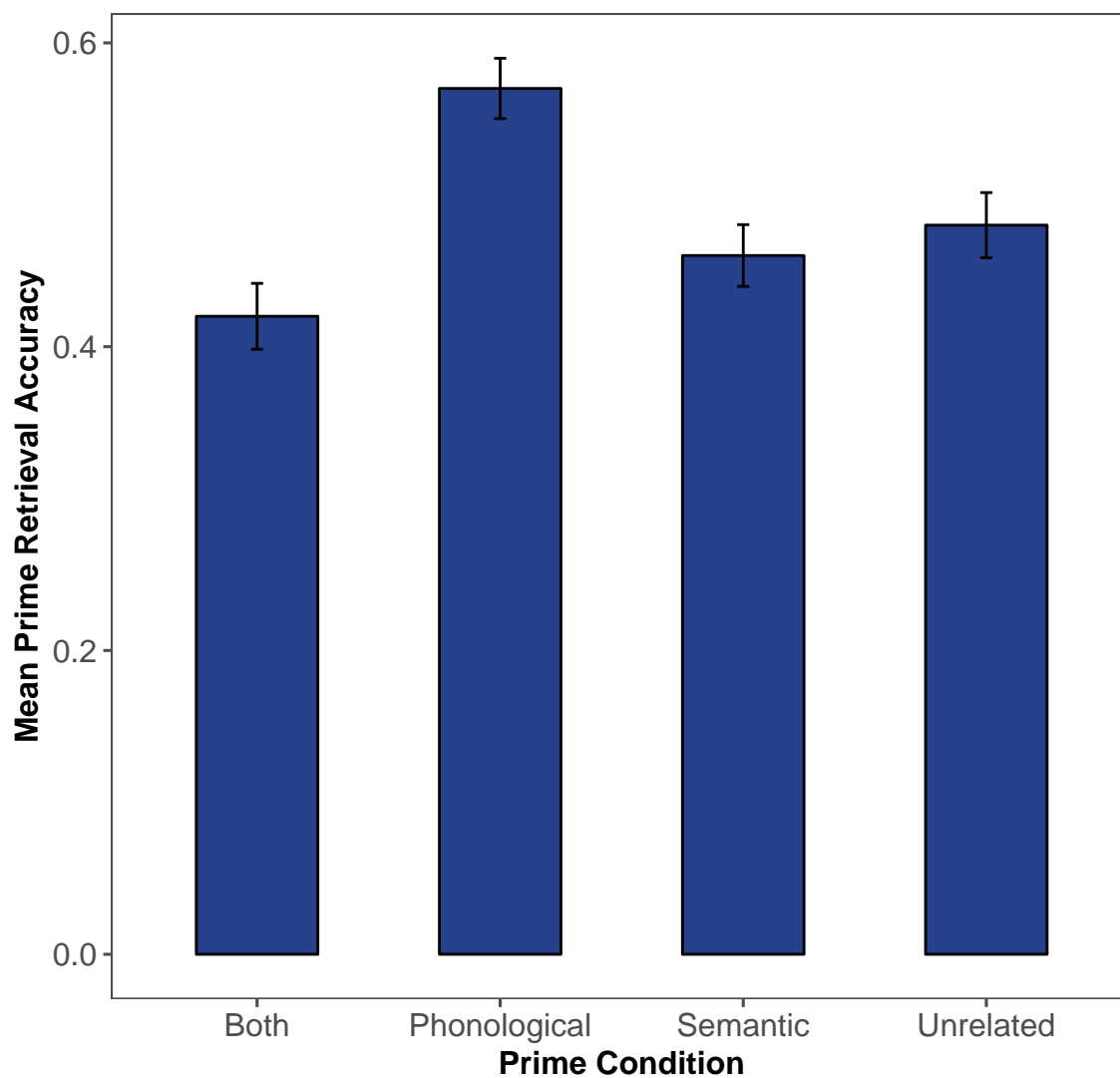
Prime

```
> agg_prime_acc = Rmisc::summarySE(agg_sub_prime,
+                               measurevar = "PrimeFirstResp_ACC",
+                               groupvars = c("PrimeCondition"))
> agg_prime_acc$PrimeFirstResp_ACC = round(agg_prime_acc$PrimeFirstResp_ACC,
+                                         digits = 2)
> library(ggplot2)
> library(ggthemes)
> agg_prime_acc %>% mutate(PrimeType = factor(PrimeCondition,
+                                           levels = unique(PrimeCondition),
```

```

+           labels = c("Both", "Phonological",
+                       "Semantic", "Unrelated")))%>%
+   ggplot(aes(x = PrimeType, y = PrimeFirstResp_ACC)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.5,
+           fill = "royalblue4", color = "black")+
+   geom_errorbar(aes(ymin = PrimeFirstResp_ACC - se,
+                     ymax = PrimeFirstResp_ACC + se),
+                 width=.05, position=position_dodge(.5)) +
+   theme_few()+
+   xlab("Prime Condition") + ylab("Mean Prime Retrieval Accuracy") +
+   ggtitle("") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
>

```



State Data

```
> state_prime_counts = group_by(PrimeRetrieval, Subject,  
+                               PrimeCondition, TargetQuestion) %>%  
+   summarise(Trials = n())  
> state_prime = Rmisc::summarySE(state_prime_counts,  
+                                measurevar = "Trials",  
+                                groupvars = c("PrimeCondition", "TargetQuestion"))  
> library(ggplot2)  
> library(ggthemes)
```

```

> state_prime %>% mutate(PrimeType = factor(PrimeCondition,
+     levels = unique(PrimeCondition),
+     labels = c("Both", "Phonological",
+     "Semantic", "Unrelated")),
+   State1 = factor(TargetQuestion, levels = unique(TargetQuestion),
+     labels = c("Know", "Dont Know",
+     "Other", "TOT")))%>%
+   ggplot(aes(x = PrimeType, y = Trials, fill = State1))+
+   geom_bar(stat = "identity", position = "dodge", width = 0.5)+
+   geom_errorbar(aes(ymin = Trials - ci, ymax = Trials + ci),
+     width=.05, position=position_dodge(.5)) +
+   scale_fill_colorblind()+
+   theme_few()+
+   xlab("Prime Condition") + ylab("Mean Number of Trials") +
+   ggtitle("YA: Target Retrieval States by Prime Condition")+
+   theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+     axis.title = element_text(face = "bold", size = rel(1.2)),
+     legend.title = element_text(face = "bold", size = rel(1.2)),
+     strip.text.x = element_text(face = "bold", size = rel(1.4)),
+     plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
>

```

3.2 Percentage State Prime Analysis

```

> state = read.csv("YAOA_agg_FINAL.csv",header = TRUE, sep = ",")
> state = state %>% filter(Age == "Young")
> j_statepercent = state[,c(2,3,160:175)] # use for prime percents
> j_statepercent$Subject = as.factor(j_statepercent$Subject)
> library(tidyr)
> library(dplyr)
> statepercent <- j_statepercent %>%
+   gather(PrimeState, Percent,
+     prop_r_know, prop_r_dontknow, prop_r_other, prop_r_TOT,
+     prop_p_know, prop_p_dontknow, prop_p_other, prop_p_TOT,
+     prop_b_know, prop_b_dontknow, prop_b_other, prop_b_TOT,
+     prop_u_know, prop_u_dontknow, prop_u_other, prop_u_TOT) %>%
+   separate(PrimeState, c('Prop', 'Prime', 'State'), sep = "_") %>%
+   arrange(Subject)
> #removing prop
> statepercent = statepercent[,-3]
> colnames(statepercent) = c("Subject", "AgeGroup",
+   "PrimeCondition", "State", "Percent")
> statepercent$AgeGroup <- as.factor(statepercent$AgeGroup)
> statepercent$Subject <- as.factor(statepercent$Subject)
> statepercent$PrimeCondition <- as.factor(statepercent$PrimeCondition)
> statepercent$State <- as.factor(statepercent$State)
> statepercent$Percent <- as.numeric(as.character(statepercent$Percent))

```



```

> ## anova
>
> state_aov = aov(data = statepercent, Percent ~ PrimeCondition*State +
+               Error(Subject/(PrimeCondition*State)))
> summary(state_aov)

Error: Subject
      Df      Sum Sq   Mean Sq F value Pr(>F)
Residuals 47 3.395e-18 7.222e-20

Error: Subject:PrimeCondition
      Df      Sum Sq   Mean Sq F value Pr(>F)
PrimeCondition  3 1.500e-19 4.991e-20  0.684  0.563
Residuals      141 1.029e-17 7.296e-20

Error: Subject:State
      Df Sum Sq Mean Sq F value Pr(>F)
State  3  10.45   3.482  44.48 <2e-16 ***
Residuals 141  11.04   0.078
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:PrimeCondition:State
      Df Sum Sq Mean Sq F value Pr(>F)
PrimeCondition:State  9  0.139 0.01549  1.118  0.348
Residuals           423  5.861 0.01385

```

3.2.1 plot

```

> ## figure
> state_rmisc = Rmisc::summarySE(statepercent,
+                               measurevar = "Percent",
+                               groupvars = c("PrimeCondition", "State"))
> x <- c("know", "dontknow", "other", "TOT")
> state_rmisc = state_rmisc %>%
+   mutate(rstate = factor(State, levels = x)) %>%
+   arrange(rstate)
> library(ggplot2)
> library(ggthemes)
> percentplot = state_rmisc %>%
+   mutate(PrimeType = factor(PrimeCondition, levels = unique(PrimeCondition),
+                             labels = c("Both", "Phonological",
+                             "Semantic", "Unrelated")),
+   R = factor(rstate, levels = unique(rstate),
+             labels = c("1: Know", "2: Dont Know",
+             "3: Other", "4: TOT")))%>%
+

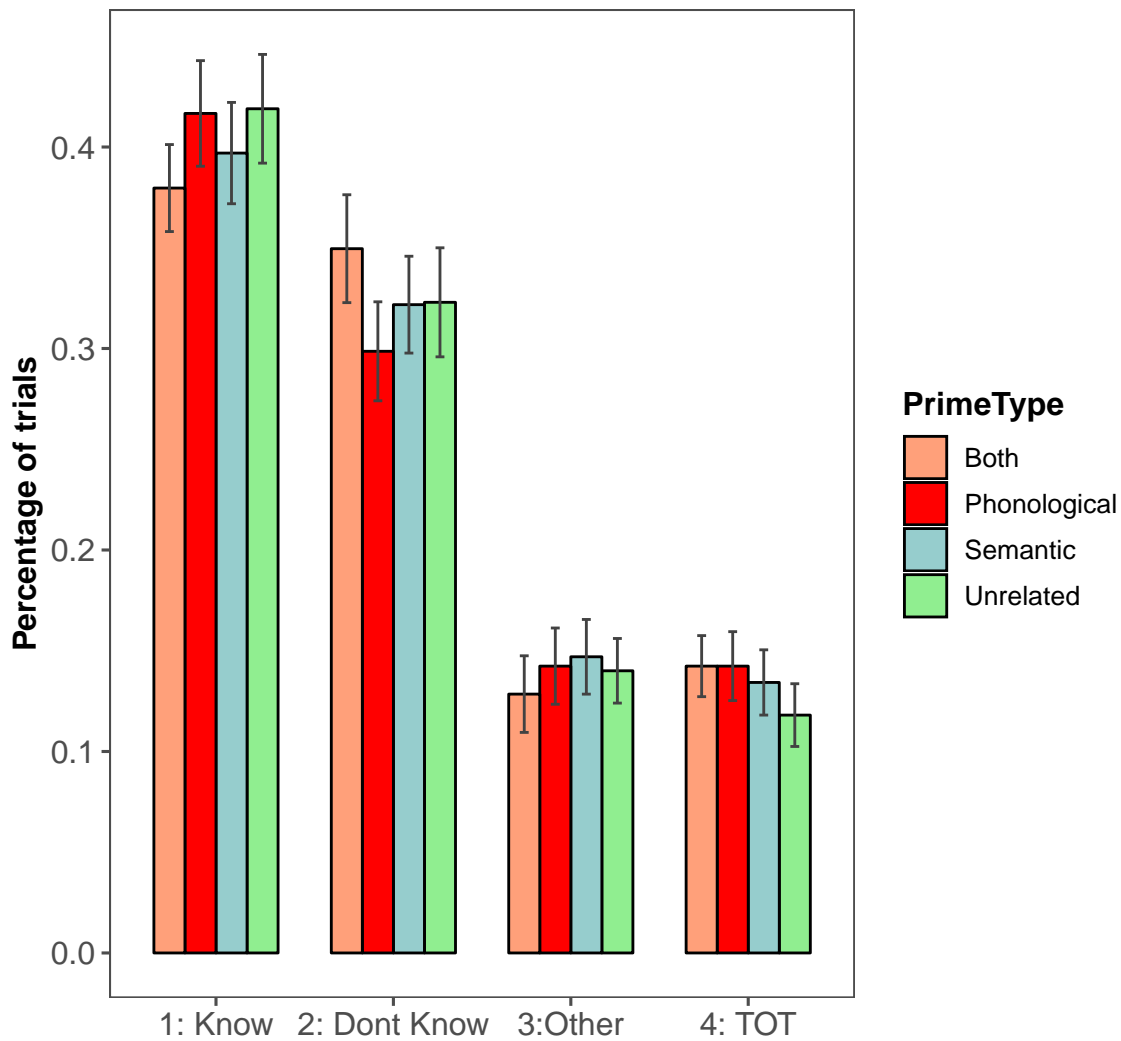
```

```

+ ggplot(aes(x = R, y = Percent,
+           group = PrimeType, fill = PrimeType))+
+   geom_bar(stat = "identity", position = "dodge", width = 0.7,
+           color= "black")+
+   geom_errorbar(aes(ymin=Percent - se, ymax=Percent + se),
+               width=.2, color = "gray26",
+               position = position_dodge(0.7))+
+   theme_few()+
+   xlab("") + ylab("Percentage of trials") +
+   scale_fill_manual(values = c( "lightsalmon", "red",
+                               "paleturquoise3","lightgreen"))+
+   ggtitle("E3: Young Adults") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         axis.text.x = element_text(size = rel(1)),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
> percentplot

```

E3: Young Adults



3.2.2 know

```
> e3_know = statepercent %>% filter(State == "know")
> e3_know_aov = aov(data = e3_know,
+                   Percent ~ PrimeCondition +
+                   Error(Subject/PrimeCondition))
> summary(e3_know_aov)
```

```
Error: Subject
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals 47  3.334  0.07094
```

```
Error: Subject:PrimeCondition
      Df Sum Sq Mean Sq F value Pr(>F)
PrimeCondition    3  0.0492  0.01639    0.99  0.399
Residuals       141  2.3343  0.01656
```

3.2.3 dont know

```
> e3_dontknow = statepercent %>% filter(State == "dontknow")
> e3_dontknow_aov = aov(data = e3_dontknow,
+                        Percent ~ PrimeCondition +
+                        Error(Subject/PrimeCondition))
> summary(e3_dontknow_aov)
```

```
Error: Subject
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals 47  4.257  0.09058

Error: Subject:PrimeCondition
      Df Sum Sq Mean Sq F value Pr(>F)
PrimeCondition    3  0.0624  0.02081    1.75  0.159
Residuals       141  1.6760  0.01189
```

3.2.4 other

```
> e3_other = statepercent %>% filter(State == "other")
> e3_other_aov = aov(data = e3_other,
+                    Percent ~ PrimeCondition +
+                    Error(Subject/PrimeCondition))
> summary(e3_other_aov)
```

```
Error: Subject
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals 47  1.846  0.03927

Error: Subject:PrimeCondition
      Df Sum Sq Mean Sq F value Pr(>F)
PrimeCondition    3  0.0089  0.002979    0.371  0.774
Residuals       141  1.1330  0.008036
```

3.2.5 TOT

```
> e3_TOT = statepercent %>% filter(State == "TOT")
> e3_TOT_aov = aov(data = e3_TOT,
+                  Percent ~ PrimeCondition +
```

```
+ Error(Subject/PrimeCondition))
> summary(e3_TOT_aov)
```

```
Error: Subject
      Df Sum Sq Mean Sq F value Pr(>F)
Residuals 47  1.599  0.03403

Error: Subject:PrimeCondition
      Df Sum Sq Mean Sq F value Pr(>F)
PrimeCondition  3 0.0189 0.006301  1.239  0.298
Residuals     141 0.7172 0.005087
```

3.3 Split by Prime and Target Accuracy

3.3.1 anova

```
> state_acc = state[,c(2,3,96:159)]
> state_acc$Subject = as.factor(state_acc$Subject)
> library(tidyr)
> library(dplyr)
> stateaccnums <- state_acc %>%
+   gather(PrimeStatePrimeRetTarget, Trials,
+         r_know_p1_t1, r_know_p1_t0, r_know_p0_t1, r_know_p0_t0,
+         p_know_p1_t1, p_know_p1_t0, p_know_p0_t1, p_know_p0_t0,
+         b_know_p1_t1, b_know_p1_t0, b_know_p0_t1, b_know_p0_t0,
+         u_know_p1_t1, u_know_p1_t0, u_know_p0_t1, u_know_p0_t0,
+         r_dontknow_p1_t1, r_dontknow_p1_t0, r_dontknow_p0_t1, r_dontknow_p0_t0,
+         p_dontknow_p1_t1, p_dontknow_p1_t0, p_dontknow_p0_t1, p_dontknow_p0_t0,
+         b_dontknow_p1_t1, b_dontknow_p1_t0, b_dontknow_p0_t1, b_dontknow_p0_t0,
+         u_dontknow_p1_t1, u_dontknow_p1_t0, u_dontknow_p0_t1, u_dontknow_p0_t0,
+         r_other_p1_t1, r_other_p1_t0, r_other_p0_t1, r_other_p0_t0,
+         p_other_p1_t1, p_other_p1_t0, p_other_p0_t1, p_other_p0_t0,
+         b_other_p1_t1, b_other_p1_t0, b_other_p0_t1, b_other_p0_t0,
+         u_other_p1_t1, u_other_p1_t0, u_other_p0_t1, u_other_p0_t0,
+         r_TOT_p1_t1, r_TOT_p1_t0, r_TOT_p0_t1, r_TOT_p0_t0,
+         p_TOT_p1_t1, p_TOT_p1_t0, p_TOT_p0_t1, p_TOT_p0_t0,
+         b_TOT_p1_t1, b_TOT_p1_t0, b_TOT_p0_t1, b_TOT_p0_t0,
+         u_TOT_p1_t1, u_TOT_p1_t0, u_TOT_p0_t1, u_TOT_p0_t0) %>%
+   separate(PrimeStatePrimeRetTarget, c( 'Prime', 'State',
+                                         'PrimeRet', 'TargetAcc'), sep = "_") %>%
+   arrange(Subject)
> stateaccnums$Subject <- as.factor(stateaccnums$Subject)
> stateaccnums$Prime <- as.factor(stateaccnums$Prime)
> stateaccnums$State <- as.factor(stateaccnums$State)
> stateaccnums$PrimeRet <- as.factor(stateaccnums$PrimeRet)
> stateaccnums$TargetAcc <- as.factor(stateaccnums$TargetAcc)
> stateaccnums$Trials <- as.numeric(as.character(stateaccnums$Trials))
```

```
> mainstate_aov = aov(data = stateaccnums,
+       Trials ~ Prime*State*PrimeRet*TargetAcc +
+       Error(Subject/(Prime*State*PrimeRet*TargetAcc)))
> summary(mainstate_aov)
```

Error: Subject

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Residuals	47	3.355e-25	7.138e-27		

Error: Subject:Prime

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Prime	3	2.960e-27	9.868e-28	0.997	0.396
Residuals	141	1.395e-25	9.895e-28		

Error: Subject:State

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
State	3	846.1	282.02	44.48	<2e-16 ***
Residuals	141	893.9	6.34		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:PrimeRet

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
PrimeRet	1	4.08	4.083	1.145	0.29
Residuals	47	167.54	3.565		

Error: Subject:TargetAcc

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
TargetAcc	1	357.5	357.5	72.4	4.48e-11 ***
Residuals	47	232.1	4.9		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:Prime:State

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Prime:State	9	11.3	1.255	1.118	0.348
Residuals	423	474.7	1.122		

Error: Subject:Prime:PrimeRet

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Prime:PrimeRet	3	49.64	16.545	15.53	8.81e-09 ***
Residuals	141	150.24	1.066		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:State:PrimeRet

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
State:PrimeRet	3	133.9	44.62	24.46	8.42e-13 ***

```

Residuals      141   257.3    1.82
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:Prime:TargetAcc
              Df Sum Sq Mean Sq F value Pr(>F)
Prime:TargetAcc  3   3.93    1.309    1.058  0.369
Residuals      141  174.45    1.237

Error: Subject:State:TargetAcc
              Df Sum Sq Mean Sq F value Pr(>F)
State:TargetAcc  3 2558.0   852.7   193.4 <2e-16 ***
Residuals      141   621.6     4.4
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:PrimeRet:TargetAcc
              Df Sum Sq Mean Sq F value    Pr(>F)
PrimeRet:TargetAcc  1   88.02    88.02   51.17 4.79e-09 ***
Residuals          47   80.85     1.72
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:Prime:State:PrimeRet
              Df Sum Sq Mean Sq F value    Pr(>F)
Prime:State:PrimeRet  9   34.7    3.857    3.246 0.000793 ***
Residuals          423   502.7     1.188
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:Prime:State:TargetAcc
              Df Sum Sq Mean Sq F value    Pr(>F)
Prime:State:TargetAcc  9    7.8    0.8701    1.012  0.429
Residuals          423   363.5    0.8594

Error: Subject:Prime:PrimeRet:TargetAcc
              Df Sum Sq Mean Sq F value    Pr(>F)
Prime:PrimeRet:TargetAcc  3   45.26   15.087   17.46 1.08e-09 ***
Residuals          141  121.86    0.864
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:State:PrimeRet:TargetAcc
              Df Sum Sq Mean Sq F value    Pr(>F)
State:PrimeRet:TargetAcc  3   50.5   16.834    7.38 0.000125 ***
Residuals          141   321.6    2.281
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
Error: Subject:Prime:State:PrimeRet:TargetAcc
              Df Sum Sq Mean Sq F value    Pr(>F)
Prime:State:PrimeRet:TargetAcc    9    37.6    4.181    4.009 6.19e-05 ***
Residuals                    423   441.2    1.043
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

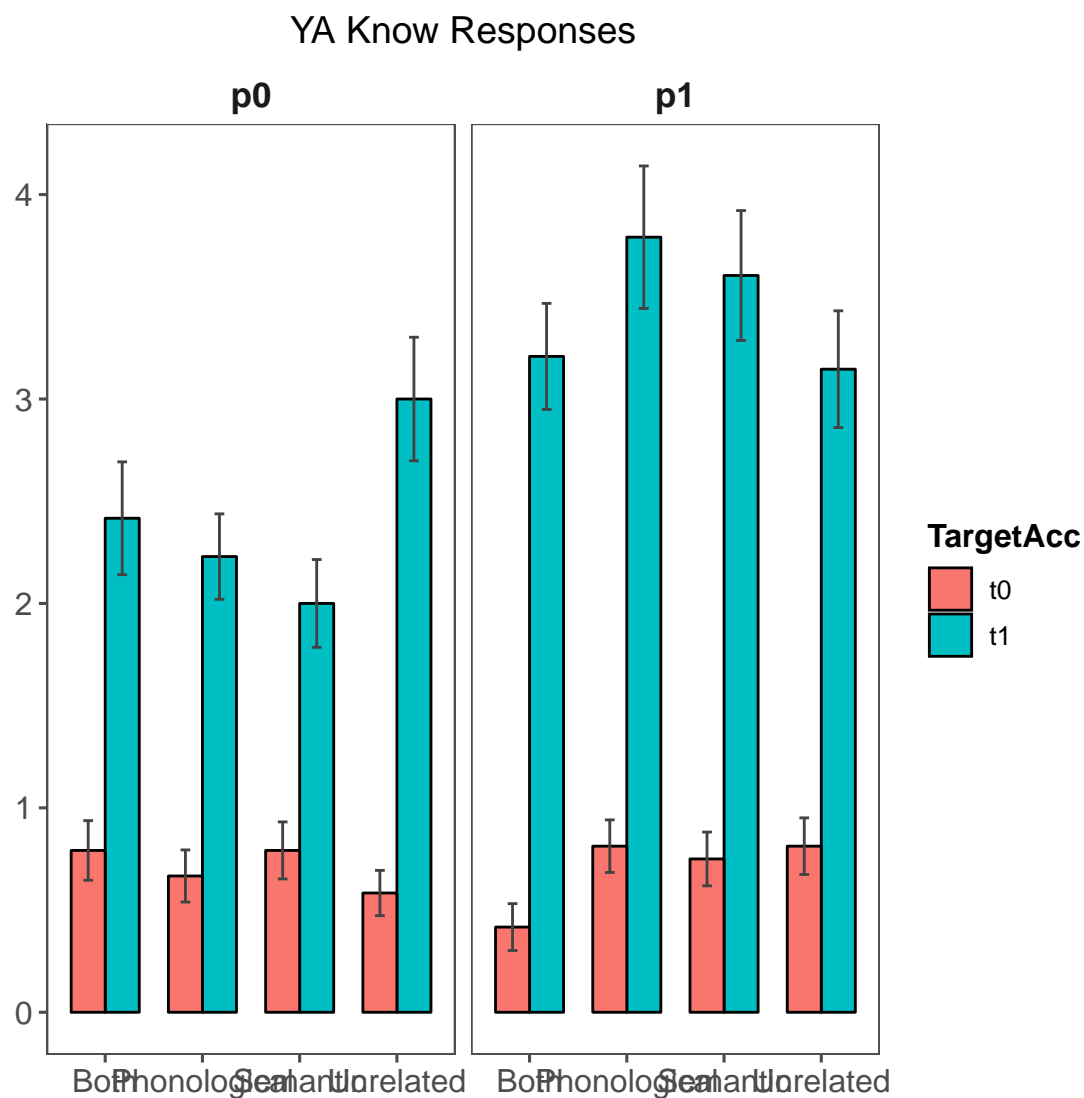
>
```

3.3.2 plot

```
> ## figure
> stateacc_rmisc = Rmisc::summarySE(stateaccnums,
+                                 measurevar = "Trials",
+                                 groupvars = c("Prime", "State",
+                                              "PrimeRet", "TargetAcc"))
> x <- c("know", "dontknow", "other", "TOT")
> stateacc_rmisc = stateacc_rmisc %>%
+   mutate(rstate = factor(State, levels = x)) %>%
+   arrange(rstate)
> know_rmisc = stateacc_rmisc %>% filter(State == "know")
> dontknow_rmisc = stateacc_rmisc %>% filter(State == "dontknow")
> other_rmisc = stateacc_rmisc %>% filter(State == "other")
> TOT_rmisc = stateacc_rmisc %>% filter(State == "TOT")
> library(ggplot2)
> library(ggthemes)
> know_percentplot = know_rmisc %>%
+   mutate(PrimeType = factor(Prime, levels = unique(Prime),
+                             labels = c("Both", "Phonological",
+                             "Semantic", "Unrelated")))%>%
+   ggplot(aes(x = PrimeType, y = Trials,
+             fill = TargetAcc, group=TargetAcc)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.7,
+           color = "black")+
+   geom_errorbar(aes(ymin=Trials - se, ymax=Trials + se),
+               width=.2, color = "gray26",
+               position = position_dodge(0.7))+
+   theme_few()+
+   facet_wrap(~PrimeRet)+
+   xlab("") + ylab("") +
+   ggtitle("YA Know Responses") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         axis.text.x = element_text(size = rel(1)),
```



```
+ strip.text.x = element_text(face = "bold", size = rel(1.4)))
> know_percentplot
```



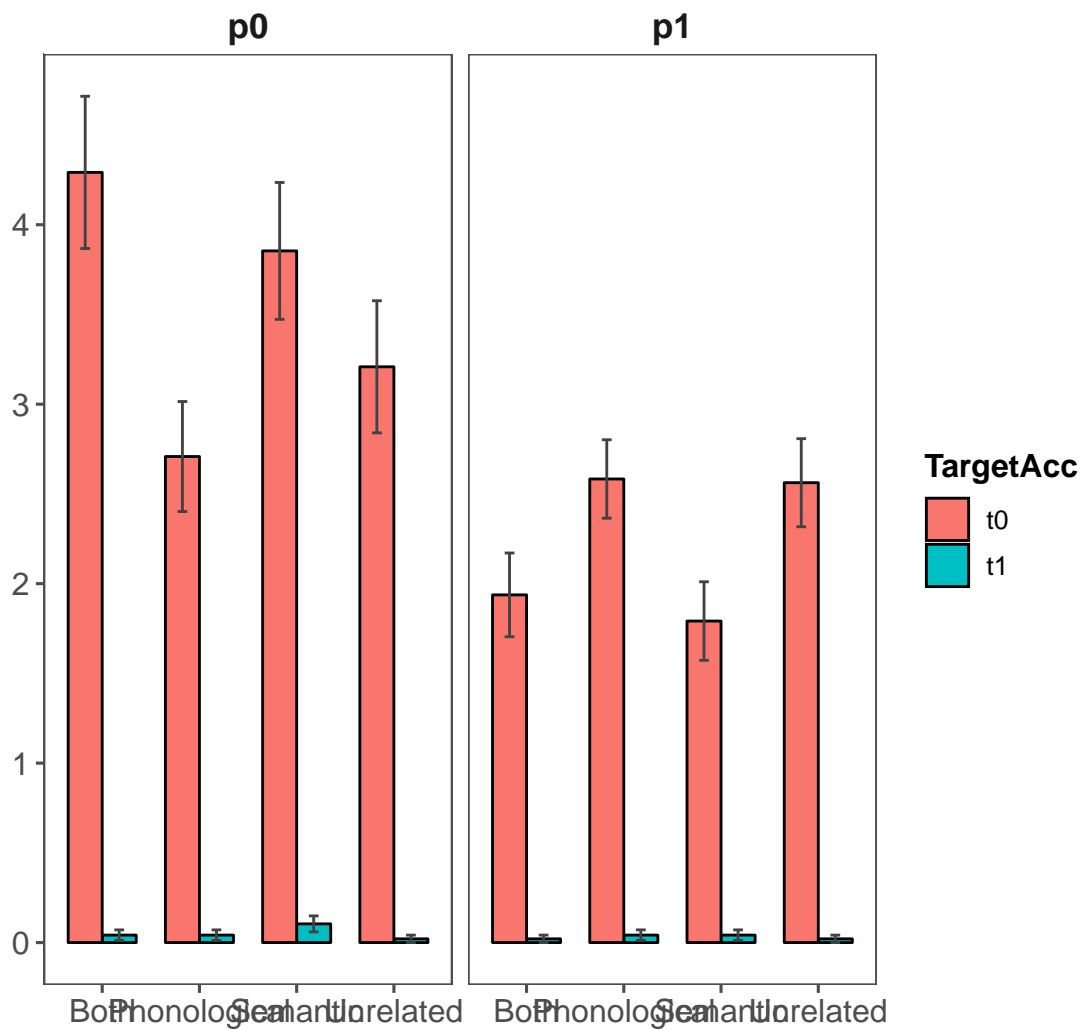
```
> dontknow_percentplot = dontknow_rmisc %>%
+ mutate(PrimeType = factor(Prime, levels = unique(Prime),
+ labels = c("Both", "Phonological",
+ "Semantic", "Unrelated")))%>%
+ ggplot(aes(x = PrimeType, y = Trials,
+ fill = TargetAcc, group=TargetAcc)) +
+ geom_bar(stat = "identity", position = "dodge", width = 0.7,
+ color= "black")+
+ strip.text.x = element_text(face = "bold", size = rel(1.4)))
```

```

+   geom_errorbar(aes(ymin=Trials - se, ymax=Trials + se),
+                 width=.2, color = "gray26",
+                 position = position_dodge(0.7))+
+   theme_few()+
+   facet_wrap(~PrimeRet)+
+   xlab("") + ylab("") +
+   ggtitle("YA Dont Know Responses") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         axis.text.x = element_text(size = rel(1)),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
> dontknow_percentplot

```

YA Dont Know Responses

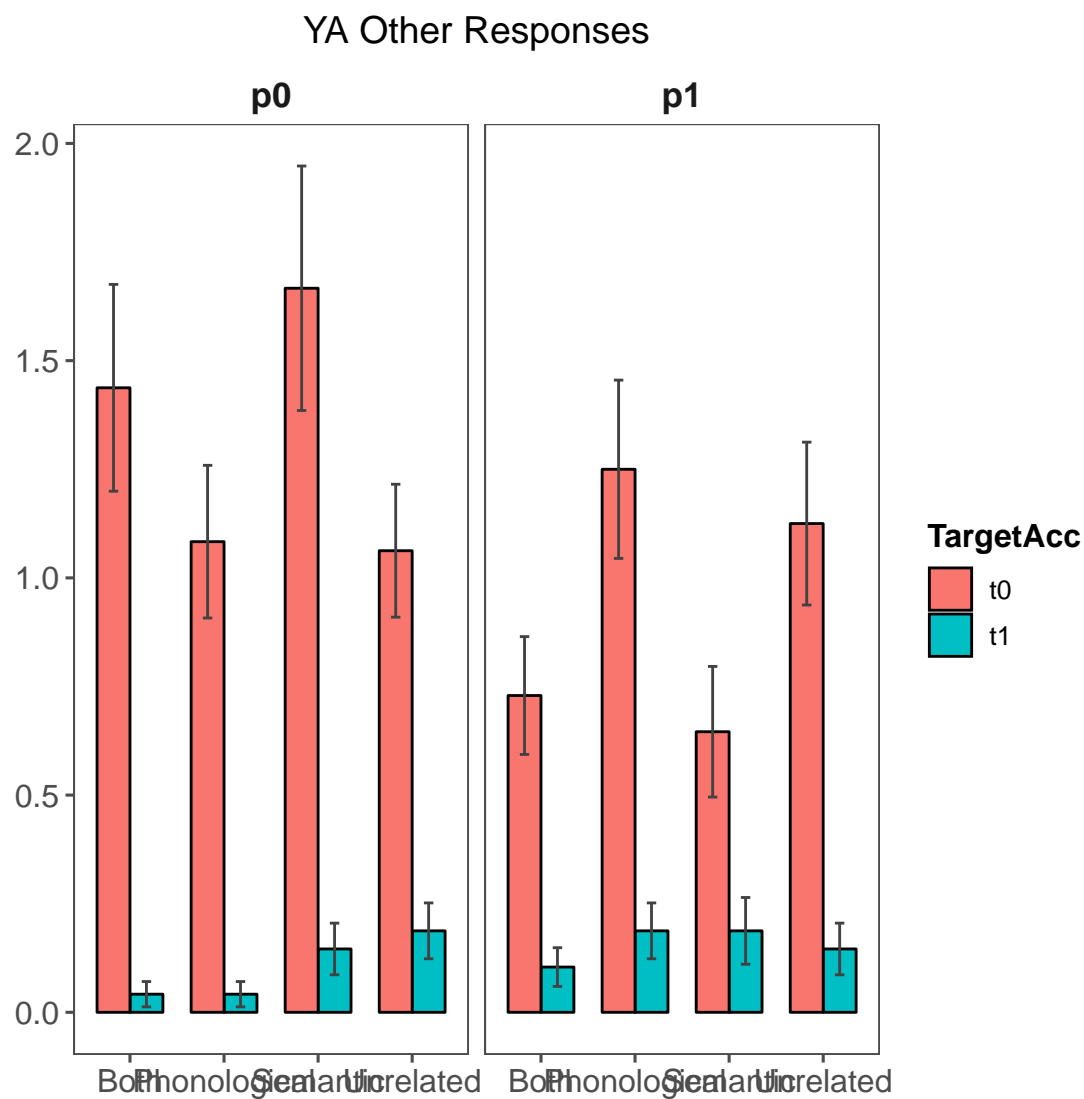


```
> other_percentplot = other_rmisc %>%
+   mutate(PrimeType = factor(Prime, levels = unique(Prime),
+                             labels = c("Both", "Phonological",
+                                         "Semantic", "Unrelated")))%>%
+   ggplot(aes(x = PrimeType, y = Trials,
+             fill = TargetAcc, group=TargetAcc)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.7,
+           color= "black")+
+   geom_errorbar(aes(ymin=Trials - se, ymax=Trials + se),
+                 width=.2, color = "gray26",
+                 position = position_dodge(0.7))+
```

```

+ theme_few()+
+ facet_wrap(~PrimeRet)+
+ xlab("") + ylab("") +
+ ggtitle("YA Other Responses") +
+ theme(axis.text = element_text(size = rel(1)),
+       axis.title = element_text(face = "bold", size = rel(1)),
+       legend.title = element_text(face = "bold", size = rel(1)),
+       plot.title = element_text(hjust = .5),
+       axis.text.x = element_text(size = rel(1)),
+       strip.text.x = element_text(face = "bold", size = rel(1.4)))
> other_percentplot

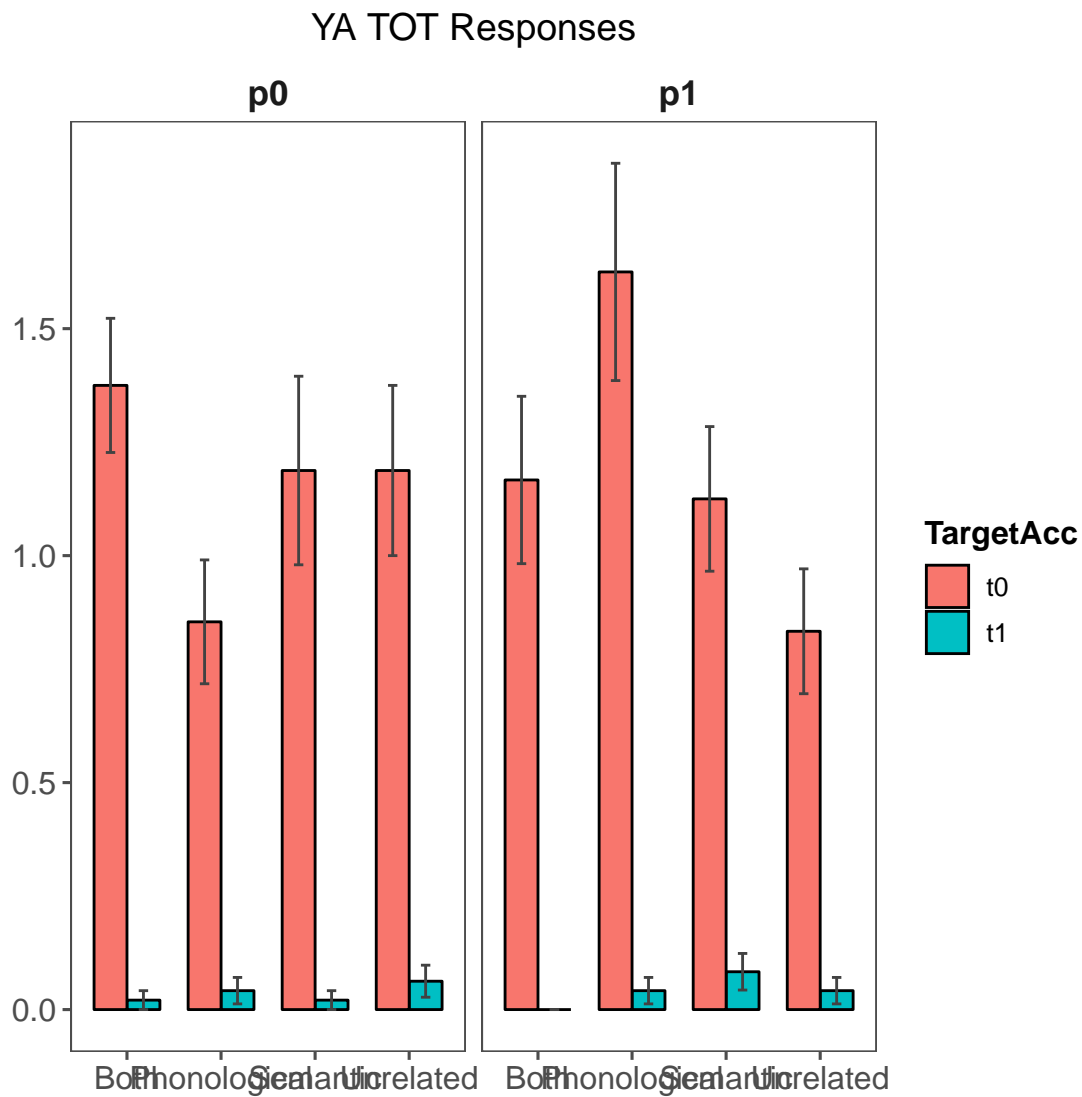
```



```

> TOT_percentplot = TOT_rmisc %>%
+   mutate(PrimeType = factor(Prime, levels = unique(Prime),
+     labels = c("Both", "Phonological",
+       "Semantic", "Unrelated")))%>%
+   ggplot(aes(x = PrimeType, y = Trials,
+     fill = TargetAcc, group=TargetAcc)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.7,
+     color= "black")+
+   geom_errorbar(aes(ymin=Trials - se, ymax=Trials + se),
+     width=.2, color = "gray26",
+     position = position_dodge(0.7))+
+   theme_few()+
+   facet_wrap(~PrimeRet)+
+   xlab("") + ylab("") +
+   ggtitle("YA TOT Responses") +
+   theme(axis.text = element_text(size = rel(1)),
+     axis.title = element_text(face = "bold", size = rel(1)),
+     legend.title = element_text(face = "bold", size = rel(1)),
+     plot.title = element_text(hjust = .5),
+     axis.text.x = element_text(size = rel(1)),
+     strip.text.x = element_text(face = "bold", size = rel(1.4)))
> TOT_percentplot

```



3.4 Split by Target Accuracy in each state

3.4.1 anova

```
> state_targetacc = state[,c(2,3,192:223)]
> state_targetacc$Subject = as.factor(state_targetacc$Subject)
> library(tidyr)
> library(dplyr)
> stateaccnums_target <- state_targetacc %>%
+   gather(PrimeStatePrimeRetTarget, Trials,
+         r_know_t1, r_know_t0,
```

```

+       p_know_t1, p_know_t0,
+       b_know_t1, b_know_t0,
+       u_know_t1, u_know_t0,
+       r_dontknow_t1, r_dontknow_t0,
+       p_dontknow_t1, p_dontknow_t0,
+       b_dontknow_t1, b_dontknow_t0,
+       u_dontknow_t1, u_dontknow_t0,
+       r_other_t1, r_other_t0,
+       p_other_t1, p_other_t0,
+       b_other_t1, b_other_t0,
+       u_other_t1, u_other_t0,
+       r_TOT_t1, r_TOT_t0,
+       p_TOT_t1, p_TOT_t0,
+       b_TOT_t1, b_TOT_t0,
+       u_TOT_t1, u_TOT_t0) %>%
+   separate(PrimeStatePrimeRetTarget, c( 'Prime', 'State',
+                                           'TargetAcc'), sep = "_") %>%
+   arrange(Subject)
> stateaccnums_target$Subject <- as.factor(stateaccnums_target$Subject)
> stateaccnums_target$Prime <- as.factor(stateaccnums_target$Prime)
> stateaccnums_target$State <- as.factor(stateaccnums_target$State)
> stateaccnums_target$TargetAcc <- as.factor(stateaccnums_target$TargetAcc)
> stateaccnums_target$Trials <- as.numeric(as.character(stateaccnums_target$Trials))
> statetargetacc_aov = aov(data = stateaccnums_target,
+                           Trials ~ Prime*State*TargetAcc +
+                           Error(Subject/(Prime*State*TargetAcc)))
> summary(statetargetacc_aov)

```

Error: Subject

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Residuals	47	1.374e-25	2.923e-27		

Error: Subject:Prime

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Prime	3	2.980e-27	9.949e-28	0.749	0.524
Residuals	141	1.872e-25	1.328e-27		

Error: Subject:State

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
State	3	1692	564.0	44.48	<2e-16 ***
Residuals	141	1788	12.7		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:TargetAcc

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
TargetAcc	1	715.0	715.0	72.4	4.48e-11 ***
Residuals	47	464.2	9.9		

```

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:Prime:State
      Df Sum Sq Mean Sq F value Pr(>F)
Prime:State    9    22.6    2.510    1.118  0.348
Residuals   423   949.4    2.244

Error: Subject:Prime:TargetAcc
      Df Sum Sq Mean Sq F value Pr(>F)
Prime:TargetAcc    3     7.9    2.618    1.058  0.369
Residuals       141   348.9    2.474

Error: Subject:State:TargetAcc
      Df Sum Sq Mean Sq F value Pr(>F)
State:TargetAcc    3   5116   1705.3   193.4 <2e-16 ***
Residuals       141   1243     8.8

---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Error: Subject:Prime:State:TargetAcc
      Df Sum Sq Mean Sq F value Pr(>F)
Prime:State:TargetAcc    9    15.7    1.740    1.012  0.429
Residuals       423   727.1    1.719

```

```
>
```

3.4.2 plot

```

> ## figure
> statetargetacc_rmisc = Rmisc::summarySE(stateaccnums_target,
+                                       measurevar = "Trials",
+                                       groupvars = c("Prime","State", "TargetAcc"))
> x <- c("know","dontknow", "other", "TOT")
> statetargetacc_rmisc = statetargetacc_rmisc %>%
+   mutate(rstate = factor(State, levels = x)) %>%
+   arrange(rstate)
> library(ggplot2)
> library(ggthemes)
> statetargetacc_plot = statetargetacc_rmisc %>%
+   mutate(PrimeType = factor(Prime, levels = unique(Prime),
+                             labels = c("Both", "Phonological",
+                             "Semantic", "Unrelated")),
+          TargetAccuracy = factor(TargetAcc, levels = unique(TargetAcc),
+                             labels = c("Failed", "Correct")),
+          R = factor(rstate, levels = unique(rstate),
+                     labels = c("1: Know","2: Dont Know",

```



```

+                                     "3:Other", "4: TOT")))%>%
+
+ ggplot(aes(x = PrimeType, y = Trials,
+           group = TargetAccuracy, fill = TargetAccuracy))+
+   geom_bar(stat = "identity", position = "dodge", width = 0.7,
+           color= "black")+
+   geom_errorbar(aes(ymin=Trials - se, ymax=Trials + se),
+                 width=.2, color = "gray26",
+                 position = position_dodge(0.7))+
+   theme_few()+
+   facet_wrap(~R)+
+   xlab("") + ylab("") +
+   ggtitle("YA States") +
+   scale_fill_wsj()+
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         axis.text.x = element_text(size = rel(1)),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
> statetargetacc_plot

```

4 Prime Demasking Analysis

```

> library(dplyr)
> PrimeRetrieval = PrimeRetrieval %>% arrange(Subject, Stimuli2)
> colnames(PrimeRetrieval) = c("Stimuli2", "PrimeCondition",
+                               "AgeGroup", "ID", "Subject",
+                               "Procedure",
+                               "Prime", "Trial",
+                               "PrimeDefResp", "PrimeFirstResp_ACC",
+                               "PrimeDefRT", "PrimeRespRESP", "PrimeRespRT",
+                               "Target", "TargetDefResp", "Accuracy",
+                               "TargetDefRT",
+                               "TargetRespRESP", "TargetRespRT",
+                               "State", "StateRT",
+                               "RTrecognisePrime", "RTrecogniseTarget",
+                               "Count", "PrimeRespType", "TargetRespType",
+                               "Prime_POS", "Target_POS",
+                               "PrimeAcc")
> #PrimeRetrieval = PrimeRetrieval %>% filter(PrimeAcc == 1)
> primewith_firsttrim_target = subset(PrimeRetrieval,
+                                     PrimeRetrieval$RTrecogniseTarget > 250 &
+                                     PrimeRetrieval$RTrecogniseTarget < 7000)
> primewith_firsttrim_prime = subset(PrimeRetrieval,
+                                    PrimeRetrieval$RTrecognisePrime > 250 &

```

```

+ PrimeRetrieval$RTrecognisePrime < 7000)
> primewith_firstttrim_targetdef = subset(PrimeRetrieval,
+ PrimeRetrieval$TargetDefRT > 250 &
+ PrimeRetrieval$TargetDefRT < 9000)

```

RTRecogniseprime

```

> ## FOR PRIME
> ## aggregate per subject all IVs and DVs
> meanRT = group_by(primewith_firstttrim_prime, Subject) %>%
+ summarise_at(vars(RTrecognisePrime), mean)
> colnames(meanRT) = c("Subject",
+ "MeanRTrecogPrime")
> sdRT = group_by(primewith_firstttrim_prime, Subject) %>%
+ summarise_at(vars(RTrecognisePrime), sd)
> colnames(sdRT) = c("Subject",
+ "sdRTrecogPrime")
> RT_agg = merge(meanRT, sdRT, by = "Subject")
> ## merge aggregate info with long data
> primewith_z_prime = merge(primewith_firstttrim_prime,
+ RT_agg, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> primewith_z_prime = primewith_z_prime %>% mutate(zPrimeRecogRT =
+ (RTrecognisePrime -
+ MeanRTrecogPrime)/sdRTrecogPrime)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(primewith_z_prime, Subject) %>%
+ summarise_at(vars(zPrimeRecogRT), mean)

```

RTRecogniseTarget

```

> ## FOR TARGET
> ## aggregate per subject all IVs and DVs
> meanRT = group_by(primewith_firstttrim_target, Subject) %>%
+ summarise_at(vars(RTrecogniseTarget), mean)
> colnames(meanRT) = c("Subject", "MeanRTrecogTarget")
> sdRT = group_by(primewith_firstttrim_target, Subject) %>%
+ summarise_at(vars(RTrecogniseTarget), sd)
> colnames(sdRT) = c("Subject", "sdRTrecogTarget")
> RT_agg = merge(meanRT, sdRT, by = "Subject")
> ## merge aggregate info with long data
> primewith_z_target= merge(primewith_firstttrim_target,
+ RT_agg, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate

```

```

> library(dplyr)
> primewith_z_target = primewith_z_target %>% mutate( zTargetRecogRT =
+                                                     (RTrecogniseTarget -
+                                                     MeanRTrecogTarget)/sdRTrecogTarget)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(primewith_z_target, Subject) %>%
+   summarise_at(vars(zTargetRecogRT), mean)
>

```

TargetDefRT

```

> ## FOR TARGET
> ## aggregate per subject all IVs and DVs
> meanRT = group_by(primewith_firsttrim_targetdef, Subject) %>%
+   summarise_at(vars(TargetDefRT), mean)
> colnames(meanRT) = c("Subject", "MeanTargetRT")
> sdRT = group_by(primewith_firsttrim_targetdef, Subject) %>%
+   summarise_at(vars(TargetDefRT), sd)
> colnames(sdRT) = c("Subject", "sdTargetRT")
> RT_agg = merge(meanRT, sdRT, by = "Subject")
> ## merge aggregate info with long data
> primewith_z_targetdef = merge(primewith_firsttrim_targetdef,
+                               RT_agg, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> primewith_z_targetdef = primewith_z_targetdef %>% mutate( zTargetRT =
+                                                         (TargetDefRT -
+                                                         MeanTargetRT)/sdTargetRT)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(primewith_z_targetdef, Subject) %>%
+   summarise_at(vars(zTargetRT), mean)
>

```

5 Trimming z-RTs

```

> #Note: We are trimming based on PrimeRecog RT because that's the RT we care about most
> primewith_z_trimmed_prime = subset(primewith_z_prime,
+                                   primewith_z_prime$zPrimeRecogRT < 3 &
+                                   primewith_z_prime$zPrimeRecogRT > -3)
> primewith_z_trimmed_target = subset(primewith_z_target,
+                                   primewith_z_target$zTargetRecogRT < 3 &
+                                   primewith_z_target$zTargetRecogRT > -3)
> primewith_z_trimmed_targetdef = subset(primewith_z_targetdef,

```

```
+
+                                     primewith_z_targetdef$zTargetRT < 3 &
+                                     primewith_z_targetdef$zTargetRT > -3)
```

6 Repeating z-scoring

6.1 For prime

```
> ## aggregate per subject all IVs and DVs
> meanRT_prime = group_by(primewith_z_trimmed_prime, Subject) %>%
+   summarise_at(vars(RTrecognisePrime), mean)
> colnames(meanRT_prime) = c("Subject",
+                             "MeanRTrecogPrime_trim")
> sdRT_prime = group_by(primewith_z_trimmed_prime, Subject) %>%
+   summarise_at(vars(RTrecognisePrime), sd)
> colnames(sdRT_prime) = c("Subject",
+                           "sdRTrecogPrime_trim")
> RT_agg_prime = merge(meanRT_prime, sdRT_prime, by = "Subject")
> ## merge aggregate info with long data
> primewith_final_z_prime = merge(primewith_z_trimmed_prime,
+                                 RT_agg_prime, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> primewith_final_z_prime = primewith_final_z_prime %>%
+   mutate( zPrimeRecogRT_trim =
+           (RTrecognisePrime -
+            MeanRTrecogPrime_trim)/sdRTrecogPrime_trim)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(primewith_final_z_prime, Subject) %>%
+   summarise_at(vars(zPrimeRecogRT_trim), mean)
>
```

6.2 For Target

```
> ## aggregate per subject all IVs and DVs
> meanRT_target = group_by(primewith_z_trimmed_target, Subject) %>%
+   summarise_at(vars(RTrecogniseTarget), mean)
> colnames(meanRT_target) = c("Subject",
+                             "MeanRTrecogTarget_trim")
> sdRT_target = group_by(primewith_z_trimmed_target, Subject) %>%
+   summarise_at(vars(RTrecogniseTarget), sd)
> colnames(sdRT_target) = c("Subject",
+                           "sdRTrecogTarget_trim")
> RT_agg_target = merge(meanRT_target, sdRT_target, by = "Subject")
> ## merge aggregate info with long data
> primewith_final_z_target = merge(primewith_z_trimmed_target,
```

```

+ RT_agg_target, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> primewith_final_z_target = primewith_final_z_target %>%
+   mutate( zTargetRecogRT_trim =
+             (RTrecogniseTarget -
+              MeanRTrecogTarget_trim)/sdRTrecogTarget_trim)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(primewith_final_z_target, Subject) %>%
+   summarise_at(vars(zTargetRecogRT_trim), mean)
>

```

6.3 For TargetDefRT

```

> ## aggregate per subject all IVs and DVs
> meanRT_targetdef = group_by(primewith_z_trimmed_targetdef, Subject) %>%
+   summarise_at(vars(TargetDefRT), mean)
> colnames(meanRT_targetdef) = c("Subject", "MeanTargetRT_trim")
> sdRT_targetdef = group_by(primewith_z_trimmed_targetdef, Subject) %>%
+   summarise_at(vars(TargetDefRT), sd)
> colnames(sdRT_targetdef) = c("Subject", "sdTargetRT_trim")
> RT_agg_targetdef = merge(meanRT_targetdef, sdRT_targetdef, by = "Subject")
> ## merge aggregate info with long data
> primewith_final_z_targetdef = merge(primewith_z_trimmed_targetdef,
+   RT_agg_targetdef, by = "Subject", all.x = T)
> ## person and grand-mean centered scores using original and aggregate
> library(dplyr)
> primewith_final_z_targetdef = primewith_final_z_targetdef %>%
+   mutate(zTargetRT_trim =
+             (TargetDefRT -
+              MeanTargetRT_trim)/sdTargetRT_trim)
> ## checking: subject level means should be zero
>
> sub_pic = group_by(primewith_final_z_targetdef, Subject) %>%
+   summarise_at(vars(zTargetRT_trim), mean)
>

```

6.4 Combining z-RT Prime and Target

```

> ## now we have separately z-scored RTprime and RTtarget. Need to combine.
> ## taking only necessary columns
> primewith_final_z_prime2 = primewith_final_z_prime[,c(1,8,35)]
> primewith_final_z = merge(primewith_final_z_target,
+   primewith_final_z_prime2,
+   by = c("Subject", "Trial"))

```

```
> primefinal_z_targetdef = merge(primewith_final_z_targetdef,
+                               primewith_final_z_prime2,
+                               by = c("Subject", "Trial"))
```

7 Linear Models

```
> # Mean RT to retrieve Target as a function of Prime Condition
>
> # Effect of RT prime on Accuracy
> library(lme4)
> RTprime_acc_model = glmer(data = primewith_final_z,
+                           Accuracy ~ zPrimeRecogRT_trim +
+                           (1|Subject) + (1|Stimuli2), family = binomial )
> summary(RTprime_acc_model)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial (logit)
Formula: Accuracy ~ zPrimeRecogRT_trim + (1 | Subject) + (1 | Stimuli2)
Data: primewith_final_z

      AIC      BIC   logLik deviance df.resid
3565.2   3589.7  -1778.6   3557.2     3348

Scaled residuals:
    Min       1Q   Median       3Q      Max
-2.9656 -0.5903 -0.3173  0.6488  5.8856

Random effects:
 Groups   Name      Variance Std.Dev.
Stimuli2 (Intercept) 1.7950   1.3398
Subject  (Intercept) 0.5028   0.7091
Number of obs: 3352, groups: Stimuli2, 72; Subject, 48

Fixed effects:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.8793     0.1943  -4.526 6.01e-06 ***
zPrimeRecogRT_trim -0.1268     0.0455  -2.786 0.00533 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
              (Intr)
zPrmRcgRT_t  0.009
```

```
> contrasts(primewith_final_z_prime$PrimeCondition) = contr.treatment(n = 4, base = 4)
```

```
> ### NOTE: for Acc analysis, use the full primewith_final_z_prime data, why exclude
> ## the RTrecogniseTarget when not using: greater power with this!
> RTprime_acc_model_2 = glmer(data = primewith_final_z_prime,
+                             Accuracy ~ zPrimeRecogRT_trim*PrimeCondition +
+                             (1|Subject) + (1|Stimuli2),
+                             family = "binomial",
+                             control=glmerControl(optimizer="bobyqa",
+                             optCtrl=list(maxfun=100000)))
> summary(RTprime_acc_model_2)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial (logit)
Formula: Accuracy ~ zPrimeRecogRT_trim * PrimeCondition + (1 | Subject) +
(1 | Stimuli2)
Data: primewith_final_z_prime
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))
```

AIC	BIC	logLik	deviance	df.resid
3583.6	3645.0	-1781.8	3563.6	3402

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.2817	-0.5794	-0.3084	0.6266	6.2235

Random effects:

Groups	Name	Variance	Std.Dev.
Stimuli2	(Intercept)	1.854	1.3614
Subject	(Intercept)	0.515	0.7176

Number of obs: 3412, groups: Stimuli2, 72; Subject, 48

Fixed effects:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.7666952	0.2097205	-3.656	0.000256 ***
zPrimeRecogRT_trim	-0.0005049	0.0877473	-0.006	0.995409
PrimeCondition1	-0.2521303	0.1209911	-2.084	0.037172 *
PrimeCondition2	-0.0830203	0.1198147	-0.693	0.488368
PrimeCondition3	-0.1793436	0.1207394	-1.485	0.137444
zPrimeRecogRT_trim:PrimeCondition1	-0.3310171	0.1306205	-2.534	0.011271 *
zPrimeRecogRT_trim:PrimeCondition2	0.0121897	0.1282882	0.095	0.924300
zPrimeRecogRT_trim:PrimeCondition3	-0.2129789	0.1279263	-1.665	0.095942 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	zPrRRT_	PrmCn1	PrmCn2	PrmCn3	zPRRT_:PC1	zPRRT_:PC2
zPrmRcgRT_t	-0.005						
PrimeCndtn1	-0.276	0.011					

```

PrimeCndtn2 -0.281 0.012 0.489
PrimeCndtn3 -0.278 0.013 0.485 0.491
zPrRRT_:PC1 0.002 -0.681 -0.002 -0.008 -0.010
zPrRRT_:PC2 0.002 -0.694 -0.010 0.058 -0.010 0.473
zPrRRT_:PC3 0.003 -0.687 -0.009 -0.009 0.049 0.470 0.479

```

```

> options(contrasts = c("contr.sum","contr.poly"))
> car::Anova(RTprime_acc_model_2)

```

Analysis of Deviance Table (Type II Wald chisquare tests)

Response: Accuracy

	Chisq	Df	Pr(>Chisq)
zPrimeRecogRT_trim	7.4749	1	0.006257 **
PrimeCondition	4.7007	3	0.195076
zPrimeRecogRT_trim:PrimeCondition	9.7558	3	0.020760 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

> anova(RTprime_acc_model_2)

```

Analysis of Variance Table

	Df	Sum Sq	Mean Sq	F value
zPrimeRecogRT_trim	1	7.3436	7.3436	7.3436
PrimeCondition	3	4.7037	1.5679	1.5679
zPrimeRecogRT_trim:PrimeCondition	3	9.8225	3.2742	3.2742

```

> # > confint(RTprime_acc_model_2)
> # Computing profile confidence intervals ...
> #
> #           2.5 %           97.5 %
> # .sig01          1.1351567  1.65598118
> # .sig02          0.5650623  0.92276591
> # (Intercept)     -1.1834774 -0.35464605
> # zPrimeRecogRT_trim      -0.1747754  0.17314296
> # PrimeCondition1      -0.4926117 -0.01292099
> # PrimeCondition2      -0.3210261  0.15457528
> # PrimeCondition3      -0.4193510  0.05985194
> # zPrimeRecogRT_trim:PrimeCondition1 -0.5915886 -0.07351300
> # zPrimeRecogRT_trim:PrimeCondition2 -0.2425930  0.26641632
> # zPrimeRecogRT_trim:PrimeCondition3 -0.4676063  0.03977605
>
> RTprime_acc_model_2_2 = glmer(data = primewith_final_z_prime,
+                               Accuracy ~ zPrimeRecogRT_trim*PrimeCondition +
+                               (1|Subject),
+                               family = binomial,
+                               control=glmerControl(optimizer="bobyqa",
+                               optCtrl=list(maxfun=100000)))
> summary(RTprime_acc_model_2_2)

```



```

Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial ( logit )
Formula: Accuracy ~ zPrimeRecogRT_trim * PrimeCondition + (1 | Subject)
Data: primewith_final_z_prime
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))

      AIC      BIC    logLik deviance df.resid
4274.9   4330.1   -2128.4   4256.9     3403

Scaled residuals:
    Min       1Q   Median       3Q      Max
-1.5798 -0.7374 -0.5527  1.1029  3.2497

Random effects:
 Groups Name      Variance Std.Dev.
Subject (Intercept) 0.2701   0.5198
Number of obs: 3412, groups: Subject, 48

Fixed effects:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.57248    0.10480   -5.463 4.69e-08 ***
zPrimeRecogRT_trim -0.01755    0.07675   -0.229  0.81916
PrimeCondition1  -0.15557    0.10535   -1.477  0.13976
PrimeCondition2  -0.07988    0.10419   -0.767  0.44326
PrimeCondition3  -0.13943    0.10486   -1.330  0.18362
zPrimeRecogRT_trim:PrimeCondition1 -0.35005    0.11021   -3.176  0.00149 **
zPrimeRecogRT_trim:PrimeCondition2 -0.09575    0.10962   -0.873  0.38240
zPrimeRecogRT_trim:PrimeCondition3 -0.33199    0.11115   -2.987  0.00282 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr) zPrRRT_ PrmCn1 PrmCn2 PrmCn3 zPRRT_:PC1 zPRRT_:PC2
zPrmRcgRT_t  0.008
PrimeCndtn1 -0.481 -0.008
PrimeCndtn2 -0.487 -0.008  0.485
PrimeCndtn3 -0.484 -0.008  0.481  0.487
zPrRRT_:PC1 -0.005 -0.699  0.002  0.006  0.006
zPrRRT_:PC2 -0.004 -0.702  0.006  0.074  0.006  0.490
zPrRRT_:PC3 -0.004 -0.692  0.006  0.006  0.082  0.484  0.485

```

```
> car::Anova(RTprime_acc_model_2_2)
```

```
Analysis of Deviance Table (Type II Wald chisquare tests)
```

```
Response: Accuracy
```

```

              Chisq Df Pr(>Chisq)
zPrimeRecogRT_trim      28.1246  1  1.137e-07 ***
PrimeCondition           2.3782  3   0.497712
zPrimeRecogRT_trim:PrimeCondition 14.7883  3   0.002007 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```
> anova(RTprime_acc_model_2_2, RTprime_acc_model_2)
```

```

Data: primewith_final_z_prime
Models:
RTprime_acc_model_2_2: Accuracy ~ zPrimeRecogRT_trim * PrimeCondition + (1 | Subject)
RTprime_acc_model_2: Accuracy ~ zPrimeRecogRT_trim * PrimeCondition + (1 | Subject) +
RTprime_acc_model_2:      (1 | Stimuli2)
              Df      AIC      BIC  logLik deviance  Chisq Chi Df
RTprime_acc_model_2_2  9 4274.9 4330.1 -2128.4  4256.9
RTprime_acc_model_2   10 3583.6 3645.0 -1781.8  3563.6 693.25      1
              Pr(>Chisq)
RTprime_acc_model_2_2
RTprime_acc_model_2   < 2.2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```

```

> y = sjPlot::plot_model(RTprime_acc_model_2, type = "int")
> y + theme_few()+
+   xlab("RT to Demask Prime") + ylab("Predicted Target Accuracy") +
+   ggtitle("YA: Target Accuracy ~ \nDemasking RT x Prime Condition") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
> RTprime_acc_model_3 = glmer(data = primewith_final_z_prime,
+   Accuracy ~ zPrimeRecogRT_trim*PrimeFirstResp_ACC*PrimeCondition +
+   (1|Subject) + (1|Stimuli2), family = "binomial",
+   control=glmerControl(optimizer="bobyqa",
+   optCtrl=list(maxfun=100000)))
> summary(RTprime_acc_model_3)

```

```

Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial ( logit )
Formula: Accuracy ~ zPrimeRecogRT_trim * PrimeFirstResp_ACC * PrimeCondition +
(1 | Subject) + (1 | Stimuli2)
Data: primewith_final_z_prime
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))

      AIC      BIC  logLik deviance df.resid

```

```

3587.5    3698.0   -1775.8    3551.5    3394

Scaled residuals:
    Min       1Q   Median       3Q      Max
-3.2062 -0.5788 -0.3041  0.6261  5.2902

Random effects:
   Groups   Name      Variance Std.Dev.
Stimuli2   (Intercept) 1.8025   1.3426
Subject    (Intercept) 0.4922   0.7016
Number of obs: 3412, groups: Stimuli2, 72; Subject, 48

Fixed effects:
                                Estimate Std. Error
(Intercept)                    -0.799660    0.211642
zPrimeRecogRT_trim              -0.014903    0.101821
PrimeFirstResp_ACC1             -0.008229    0.097069
PrimeCondition1                  -0.291344    0.140179
PrimeCondition2                  -0.067197    0.134560
PrimeCondition3                  -0.132196    0.137570
zPrimeRecogRT_trim:PrimeFirstResp_ACC1  0.087752    0.102876
zPrimeRecogRT_trim:PrimeCondition1     -0.278557    0.152503
zPrimeRecogRT_trim:PrimeCondition2      0.034654    0.143395
zPrimeRecogRT_trim:PrimeCondition3     -0.104447    0.145961
PrimeFirstResp_ACC1:PrimeCondition1    -0.175200    0.143707
PrimeFirstResp_ACC1:PrimeCondition2    -0.022500    0.138736
PrimeFirstResp_ACC1:PrimeCondition3    -0.213980    0.140863
zPrimeRecogRT_trim:PrimeFirstResp_ACC1:PrimeCondition1  0.093286    0.151875
zPrimeRecogRT_trim:PrimeFirstResp_ACC1:PrimeCondition2 -0.041207    0.142383
zPrimeRecogRT_trim:PrimeFirstResp_ACC1:PrimeCondition3 -0.092252    0.146773

                                z value Pr(>|z|)
(Intercept)                    -3.778 0.000158 ***
zPrimeRecogRT_trim              -0.146 0.883636
PrimeFirstResp_ACC1             -0.085 0.932443
PrimeCondition1                  -2.078 0.037675 *
PrimeCondition2                  -0.499 0.617510
PrimeCondition3                  -0.961 0.336587
zPrimeRecogRT_trim:PrimeFirstResp_ACC1  0.853 0.393666
zPrimeRecogRT_trim:PrimeCondition1     -1.827 0.067765 .
zPrimeRecogRT_trim:PrimeCondition2      0.242 0.809035
zPrimeRecogRT_trim:PrimeCondition3     -0.716 0.474248
PrimeFirstResp_ACC1:PrimeCondition1    -1.219 0.222790
PrimeFirstResp_ACC1:PrimeCondition2    -0.162 0.871164
PrimeFirstResp_ACC1:PrimeCondition3    -1.519 0.128747
zPrimeRecogRT_trim:PrimeFirstResp_ACC1:PrimeCondition1  0.614 0.539063
zPrimeRecogRT_trim:PrimeFirstResp_ACC1:PrimeCondition2 -0.289 0.772269
zPrimeRecogRT_trim:PrimeFirstResp_ACC1:PrimeCondition3 -0.629 0.529650
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> car::Anova(RTprime_acc_model_3)
```

```
Analysis of Deviance Table (Type II Wald chisquare tests)
```

```
Response: Accuracy
```

	Chisq	Df	Pr(>Chisq)
zPrimeRecogRT_trim	2.0263	1	0.15459
PrimeFirstResp_ACC	5.2388	1	0.02209 *
PrimeCondition	4.6224	3	0.20163
zPrimeRecogRT_trim:PrimeFirstResp_ACC	1.9268	1	0.16511
zPrimeRecogRT_trim:PrimeCondition	4.4479	3	0.21699
PrimeFirstResp_ACC:PrimeCondition	3.4170	3	0.33168
zPrimeRecogRT_trim:PrimeFirstResp_ACC:PrimeCondition	1.5861	3	0.66255

```
---
```

```
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> z = sjPlot::plot_model(RTprime_acc_model_3, type = "int",
+                         terms = c("zPrimeRecogRT_trim", "PrimeFirstResp_ACC"))
> z + theme_few()+
+   xlab("RT to Demask Prime") + ylab("Predicted Target Accuracy") +
+   ggtitle("YA: Target Accuracy ~ \nDemasking RT x Prime Condition x Prime Retrieval Accu")
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)))
> anova(RTprime_acc_model_2, RTprime_acc_model_3)
```

```
Data: primewith_final_z_prime
```

```
Models:
```

```
RTprime_acc_model_2: Accuracy ~ zPrimeRecogRT_trim * PrimeCondition + (1 | Subject) +
RTprime_acc_model_2: (1 | Stimuli2)
RTprime_acc_model_3: Accuracy ~ zPrimeRecogRT_trim * PrimeFirstResp_ACC * PrimeCondition
RTprime_acc_model_3: (1 | Subject) + (1 | Stimuli2)
```

	Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
RTprime_acc_model_2	10	3583.6	3645	-1781.8	3563.6				
RTprime_acc_model_3	18	3587.5	3698	-1775.8	3551.5	12.129		8	0.1455

```
>
```

7.1 Effect of Prime RT on Target RT

```
> library(lme4)
> library(lmerTest)
```

```
> contrasts(primewith_final_z$PrimeCondition) = contr.treatment(n = 4, base = 4)
> RTprime_RT_model_2 = lmer(data = primewith_final_z,
+                             zTargetRecogRT_trim ~ zPrimeRecogRT_trim*PrimeCondition +
+                             (1|Subject) + (1|Stimuli2))
> summary(RTprime_RT_model_2)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: zTargetRecogRT_trim ~ zPrimeRecogRT_trim * PrimeCondition + (1 |
  Subject) + (1 | Stimuli2)
Data: primewith_final_z

REML criterion at convergence: 8464.6

Scaled residuals:
    Min       1Q   Median       3Q      Max
-3.2682 -0.6667 -0.1178  0.5877  4.4333

Random effects:
   Groups      Name      Variance Std.Dev.
Stimuli2 (Intercept) 0.2953    0.5434
Subject   (Intercept) 0.0000    0.0000
Residual                  0.6788    0.8239
Number of obs: 3352, groups: Stimuli2, 72; Subject, 48

Fixed effects:
              Estimate Std. Error      df t value
(Intercept)      0.02964    0.07010   91.94932    0.423
zPrimeRecogRT_trim      0.06724    0.03018 3285.20340    2.228
PrimeCondition1     -0.04970    0.04052 3273.61861   -1.227
PrimeCondition2     -0.03517    0.04048 3272.91098   -0.869
PrimeCondition3      0.01614    0.04024 3272.76873    0.401
zPrimeRecogRT_trim:PrimeCondition1    0.10499    0.04213 3298.55774    2.492
zPrimeRecogRT_trim:PrimeCondition2    0.04839    0.04366 3295.77421    1.108
zPrimeRecogRT_trim:PrimeCondition3    0.07813    0.04245 3292.06652    1.840
              Pr(>|t|)
(Intercept)      0.6734
zPrimeRecogRT_trim      0.0259 *
PrimeCondition1      0.2200
PrimeCondition2      0.3851
PrimeCondition3      0.6885
zPrimeRecogRT_trim:PrimeCondition1    0.0128 *
zPrimeRecogRT_trim:PrimeCondition2    0.2678
zPrimeRecogRT_trim:PrimeCondition3    0.0658 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
```

```

      (Intr) zPrRRT_ PrmCn1 PrmCn2 PrmCn3 zPRRT_:PC1 zPRRT_:PC2
zPrmRcgRT_t    0.001
PrimeCndtn1 -0.286  0.000
PrimeCndtn2 -0.287 -0.001    0.496
PrimeCndtn3 -0.288 -0.001    0.499    0.499
zPrRRT_:PC1   0.000 -0.725  -0.071    0.001    0.000
zPrRRT_:PC2   0.000 -0.701  -0.002    0.061  -0.001    0.512
zPrRRT_:PC3  -0.001 -0.707    0.000    0.002    0.023    0.514        0.500

```

```
> car::Anova(RTprime_RT_model_2)
```

Analysis of Deviance Table (Type II Wald chisquare tests)

Response: zTargetRecogRT_trim

	Chisq	Df	Pr(>Chisq)
zPrimeRecogRT_trim	70.1551	1	< 2e-16 ***
PrimeCondition	2.8380	3	0.41728
zPrimeRecogRT_trim:PrimeCondition	6.8156	3	0.07801 .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> options(contrasts = c("contr.sum","contr.poly"))
```

```
> anova(RTprime_RT_model_2)
```

Type III Analysis of Variance Table with Satterthwaite's method

	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)
zPrimeRecogRT_trim	46.913	46.913	1	3297.6	69.1120	< 2e-16
PrimeCondition	2.314	0.771	3	3273.3	1.1363	0.33292
zPrimeRecogRT_trim:PrimeCondition	4.626	1.542	3	3297.4	2.2719	0.07822

zPrimeRecogRT_trim ***

PrimeCondition

zPrimeRecogRT_trim:PrimeCondition .

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> # > confint(RTprime_RT_model_2)
```

```
> # Computing profile confidence intervals ...
```

	2.5 %	97.5 %
# .sig01	0.457422647	0.64602628
# .sig02	0.000000000	0.02942538
# .sigma	0.803488757	0.84333785
# (Intercept)	-0.108282360	0.16762085
# zPrimeRecogRT_trim	0.008125974	0.12633493
# PrimeCondition1	-0.129050764	0.02964582
# PrimeCondition2	-0.114453497	0.04412090
# PrimeCondition3	-0.062682860	0.09495232

```

> # zPrimeRecogRT_trim:PrimeCondition1 0.022506875 0.18754099
> # zPrimeRecogRT_trim:PrimeCondition2 -0.037073414 0.13395257
> # zPrimeRecogRT_trim:PrimeCondition3 -0.004960774 0.16134136
>
> RTprime_RT_model_1 = lmer(data = primewith_final_z,
+                             zTargetRecogRT_trim ~ PrimeCondition +
+                             (1|Subject) + (1|Stimuli2))
> summary(RTprime_RT_model_1)

```

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
Formula: zTargetRecogRT_trim ~ PrimeCondition + (1 | Subject) + (1 | Stimuli2)
Data: primewith_final_z

```

```
REML criterion at convergence: 8520.1
```

```
Scaled residuals:
```

Min	1Q	Median	3Q	Max
-3.0891	-0.6751	-0.1183	0.5899	4.8914

```
Random effects:
```

Groups	Name	Variance	Std.Dev.
Stimuli2	(Intercept)	0.3072	0.5543
Subject	(Intercept)	0.0000	0.0000
Residual		0.6933	0.8327

```
Number of obs: 3352, groups: Stimuli2, 72; Subject, 48
```

```
Fixed effects:
```

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	0.02931	0.07140	91.63782	0.411	0.682
PrimeCondition1	-0.02500	0.04073	3276.93776	-0.614	0.539
PrimeCondition2	-0.04768	0.04077	3276.99052	-1.169	0.242
PrimeCondition3	0.01046	0.04065	3276.78506	0.257	0.797

```
Correlation of Fixed Effects:
```

	(Intr)	PrmCn1	PrmCn2
PrimeCndtn1	-0.286		
PrimeCndtn2	-0.285	0.500	
PrimeCndtn3	-0.286	0.502	0.501

```
> anova(RTprime_RT_model_1, RTprime_RT_model_2)
```

```
Data: primewith_final_z
```

```
Models:
```

```
RTprime_RT_model_1: zTargetRecogRT_trim ~ PrimeCondition + (1 | Subject) + (1 | Stimuli2)
```

```
RTprime_RT_model_2: zTargetRecogRT_trim ~ zPrimeRecogRT_trim * PrimeCondition + (1 |
```

```
RTprime_RT_model_2: Subject) + (1 | Stimuli2)
```

Df	AIC	BIC	logLik	deviance	Chisq	Chi	Df	Pr(>Chisq)
----	-----	-----	--------	----------	-------	-----	----	------------

```
RTprime_RT_model_1 7 8516.1 8558.9 -4251.0 8502.1
RTprime_RT_model_2 11 8447.8 8515.1 -4212.9 8425.8 76.285 4 1.066e-15

RTprime_RT_model_1
RTprime_RT_model_2 ***
---
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
> car::Anova(RTprime_RT_model_1)
```

```
Analysis of Deviance Table (Type II Wald chisquare tests)
```

```
Response: zTargetRecogRT_trim
          Chisq Df Pr(>Chisq)
PrimeCondition 2.4645 3 0.4817
```

```
>
```

7.2 Contrast Codes

```
> RT_fixedeff = matrix(fixef(RTprime_acc_model_2))
> both = RT_fixedeff[1]
> phon = RT_fixedeff[1] + RT_fixedeff[3]
> sem = RT_fixedeff[1] + RT_fixedeff[4]
> unrel = RT_fixedeff[1] + RT_fixedeff[5]
> final_means = as.data.frame(rbind(both, phon, sem, unrel))
> final_means$odds = exp(final_means$V1)
> final_means$prob = final_means$odds/(1+final_means$odds)
>
```

7.3 Collapsing P and U conditions

```
> primewith_final_z$NewPrimes = ifelse(primewith_final_z$PrimeCondition == "P" |
+   primewith_final_z$PrimeCondition == "U", "Unrelated",
+   ifelse(primewith_final_z$PrimeCondition == "B",
+   "Both", "Semantic" ))
> RTprime_acc_model_2_new = glmer(data = primewith_final_z,
+   Accuracy ~ zPrimeRecogRT_trim*NewPrimes +
+   (1|Subject) + (1|Stimuli2), family = binomial )
> summary(RTprime_acc_model_2_new)
```

```
Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial ( logit )
Formula: Accuracy ~ zPrimeRecogRT_trim * NewPrimes + (1 | Subject) + (1 |
```



```

Stimuli2)
Data: primewith_final_z

      AIC      BIC    logLik deviance df.resid
3559.1    3608.1   -1771.6    3543.1     3344

Scaled residuals:
      Min       1Q   Median       3Q      Max
-3.2033 -0.5883 -0.3116  0.6398  5.8780

Random effects:
Groups      Name      Variance Std.Dev.
Stimuli2 (Intercept) 1.8020    1.3424
Subject  (Intercept) 0.5054    0.7109
Number of obs: 3352, groups: Stimuli2, 72; Subject, 48

Fixed effects:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)   -0.90559    0.19535  -4.636 3.56e-06 ***
zPrimeRecogRT_trim -0.17658    0.04939  -3.576 0.000349 ***
NewPrimes1    -0.10179    0.06785  -1.500 0.133530
NewPrimes2    -0.01741    0.06767  -0.257 0.796916
zPrimeRecogRT_trim:NewPrimes1 -0.15645    0.07434  -2.105 0.035334 *
zPrimeRecogRT_trim:NewPrimes2 -0.02908    0.07287  -0.399 0.689883
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
              (Intr) zPrRRT_ NwPrm1 NwPrm2 zPRRT_:NP1
zPrmRcgRT_t   0.011
NewPrimes1    0.036 -0.032
NewPrimes2    0.033  0.052 -0.644
zPrRRT_:NP1  -0.008  0.175  0.040 -0.045
zPrRRT_:NP2   0.012  0.133 -0.044  0.094 -0.651

> car::Anova(RTprime_acc_model_2_new)

Analysis of Deviance Table (Type II Wald chisquare tests)

Response: Accuracy

              Chisq Df Pr(>Chisq)
zPrimeRecogRT_trim    6.9553  1  0.008357 **
NewPrimes              4.2522  2  0.119299
zPrimeRecogRT_trim:NewPrimes 9.8484  2  0.007269 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

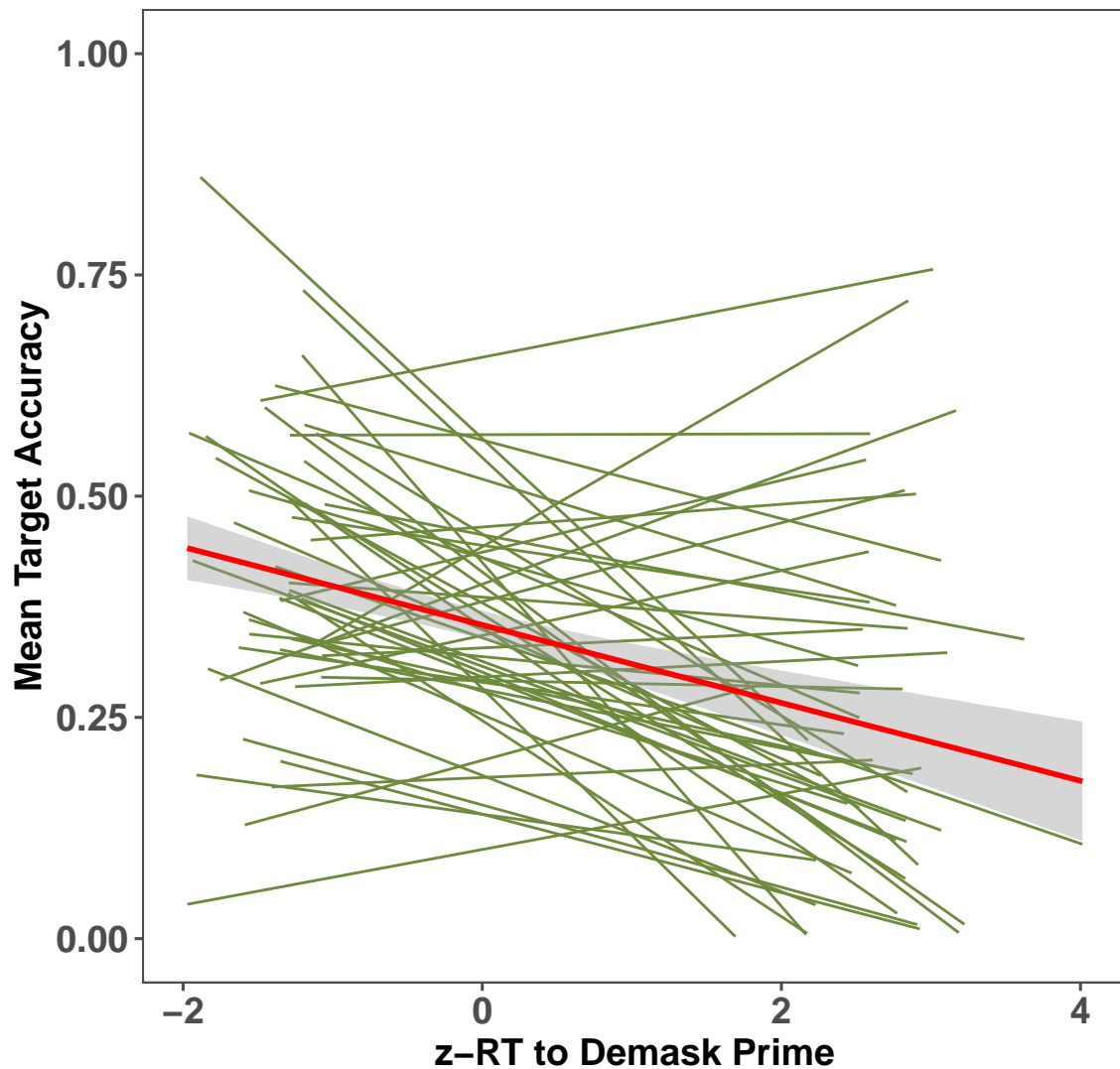
```

8 Plotting Raw Data

8.1 Model 1

```
> library(ggplot2)
> library(ggthemes)
> mainplot = primewith_final_z %>%
+   ggplot(aes(x = zPrimeRecogRT_trim , y = Accuracy,
+             group = factor(Subject))) +
+   geom_smooth(method = "lm", se = FALSE, color = "darkolivegreen4", size = 0.5)+
+   guides(color = FALSE)+
+   xlab("z-RT to Demask Prime") + ylab ("Mean Target Accuracy")+
+   ggtitle("YA: Target Accuracy by Prime Demasking RT")+
+   theme_few() +
+   ylim(0,1) +
+   theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+         axis.title = element_text(face = "bold", size = rel(1.2)),
+         legend.title = element_text(face = "bold", size = rel(1.2)),
+         plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
> mainplot + stat_smooth(aes(group = 1), method = "lm", color = "red")
>
```

YA: Target Accuracy by Prime Demasking RT



8.2 Model 2

```
> ## sd for zPrimeRecogRT_trim  
> sd(primewith_final_z_prime$zPrimeRecogRT_trim)
```

```
[1] 0.9930866
```

```
> # this is the model  
>  
> # RTprime_acc_model_2 = glmer(data = primewith_final_z_prime ,
```

```

> # Accuracy ~ zPrimeRecogRT_trim*PrimeCondition +
> # (1|Subject) + (1|Stimuli2),
> # family = "binomial",
> # control=glmerControl(optimizer="bobyqa",
> # optCtrl=list(maxfun=100000)))
> # summary(RTprime_acc_model_2)
>
> primert_model = lmer(data = primewith_final_z_prime,
+ zPrimeRecogRT_trim ~ 1 + (1 | Subject) +
+ (1|Stimuli2))
> summary(primert_model)

```

Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]

Formula: zPrimeRecogRT_trim ~ 1 + (1 | Subject) + (1 | Stimuli2)
Data: primewith_final_z_prime

REML criterion at convergence: 9521.4

Scaled residuals:

Min	1Q	Median	3Q	Max
-2.1255	-0.7335	-0.2088	0.5849	4.1482

Random effects:

Groups	Name	Variance	Std.Dev.
Stimuli2	(Intercept)	0.06299	0.2510
Subject	(Intercept)	0.00000	0.0000
Residual		0.92414	0.9613

Number of obs: 3412, groups: Stimuli2, 72; Subject, 48

Fixed effects:

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	7.774e-04	3.385e-02	7.097e+01	0.023	0.982

```

> VarCorr(primert_model)

```

Groups	Name	Std.Dev.
Stimuli2	(Intercept)	0.25097
Subject	(Intercept)	0.00000
Residual		0.96132

```

> SD_prime <- as.data.frame(VarCorr(primert_model))[3, 5]
> ## now we need to find increments for each prime condition
>
> primert_model_2 <- lmer(data = primewith_final_z_prime,
+ zPrimeRecogRT_trim ~ 1 + PrimeCondition +
+ (1|Subject) + (1|Stimuli2))
> prime_inc_1_U <- 0*fixef(primert_model_2)[1]

```

```

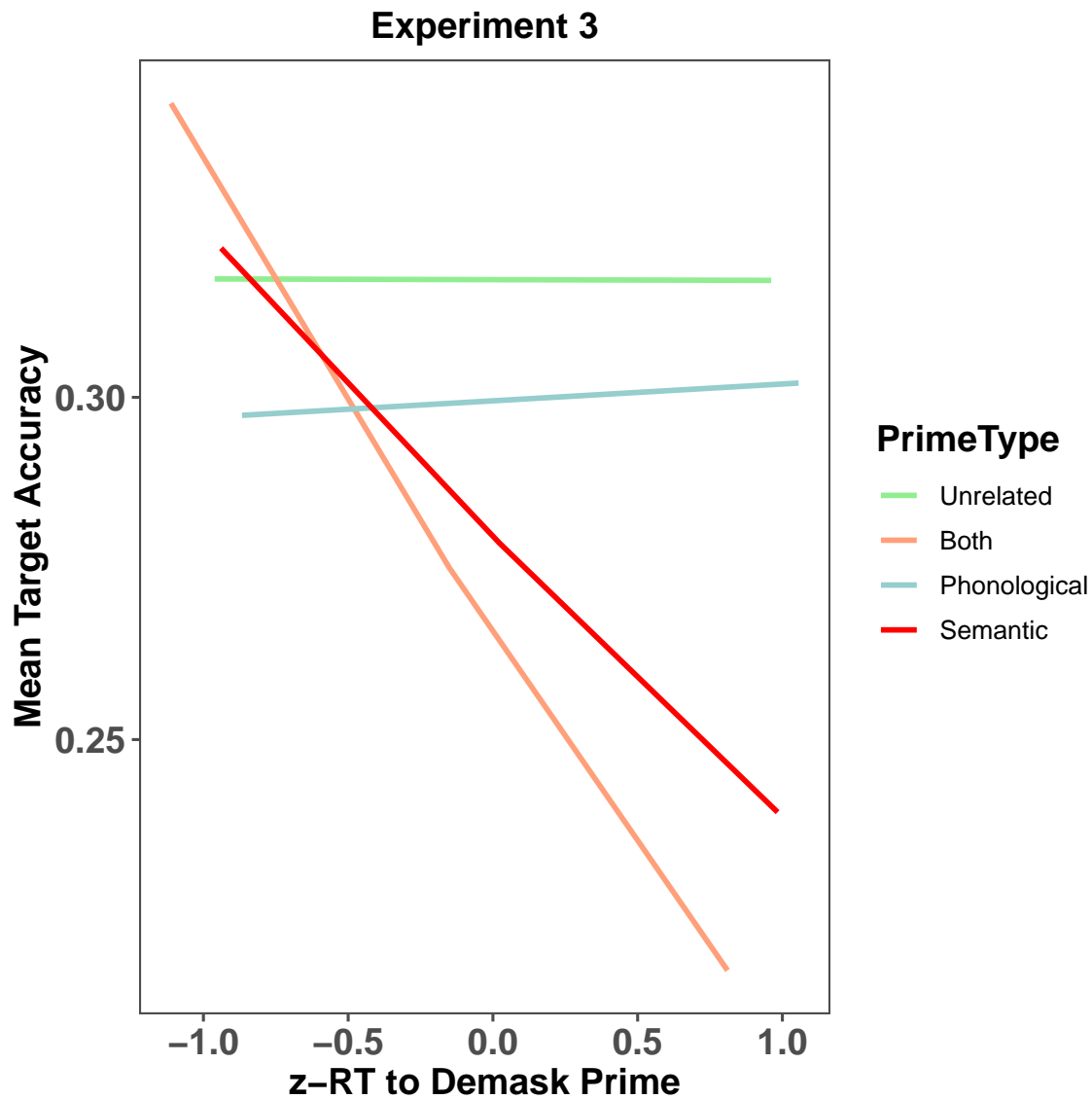
> prime_Inc_1_B <- 1*fixef(primert_model_2)[2]
> prime_Inc_1_P <- 1*fixef(primert_model_2)[3]
> prime_Inc_1_R <- 1*fixef(primert_model_2)[4]
> predict_data_U <- with(primewith_final_z_prime,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_U-SD_prime,
+ to=-prime_Inc_1_U+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 0))
> predict_data_B <- with(primewith_final_z_prime,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_B-SD_prime,
+ to=-prime_Inc_1_B+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 1))
> predict_data_P <- with(primewith_final_z_prime,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_P-SD_prime,
+ to=-prime_Inc_1_P+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 2))
> predict_data_R <- with(primewith_final_z_prime,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_R-SD_prime,
+ to=-prime_Inc_1_R+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 3))
> predict_data = rbind(predict_data_U,
+ predict_data_B,
+ predict_data_P,
+ predict_data_R)
> predict_data$PrimeCondition = ifelse(predict_data$PrimeCondition == 0, "U",
+ ifelse(predict_data$PrimeCondition == 1, "B",
+ ifelse(predict_data$PrimeCondition == 2, "P", "R")))
> predict_data = predict_data %>%
+ mutate(predicted_values = predict(RTprime_acc_model_2,
+ newdata = predict_data, re.form = NA))
> predict_data$prob = exp(predict_data$predicted_values)/(1+exp(predict_data$predicted_v
> predict_data$PrimeCondition = ordered(as.factor(as.character(predict_data$PrimeCondi
> predict_data %>%
+ mutate(PrimeType = factor(PrimeCondition, levels = unique(PrimeCondition),
+ labels = c("Unrelated",
+ "Both", "Phonological", "Semantic"))))%>%
+ ggplot(aes(x = zPrimeRecogRT_trim, y = prob,
+ color = PrimeType)) +
+ geom_line(size = 1) +
+ xlab("z-RT to Demask Prime") + ylab ("Mean Target Accuracy")+
+ ggtitle("Experiment 3")+

```

```

+ theme_few() +
+   scale_color_manual(values = c( "lightgreen", "lightsalmon",
+                                   "paleturquoise3","red"))+
+   theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+         axis.title = element_text(face = "bold", size = rel(1.2)),
+         legend.title = element_text(face = "bold", size = rel(1.2)),
+         plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))

```



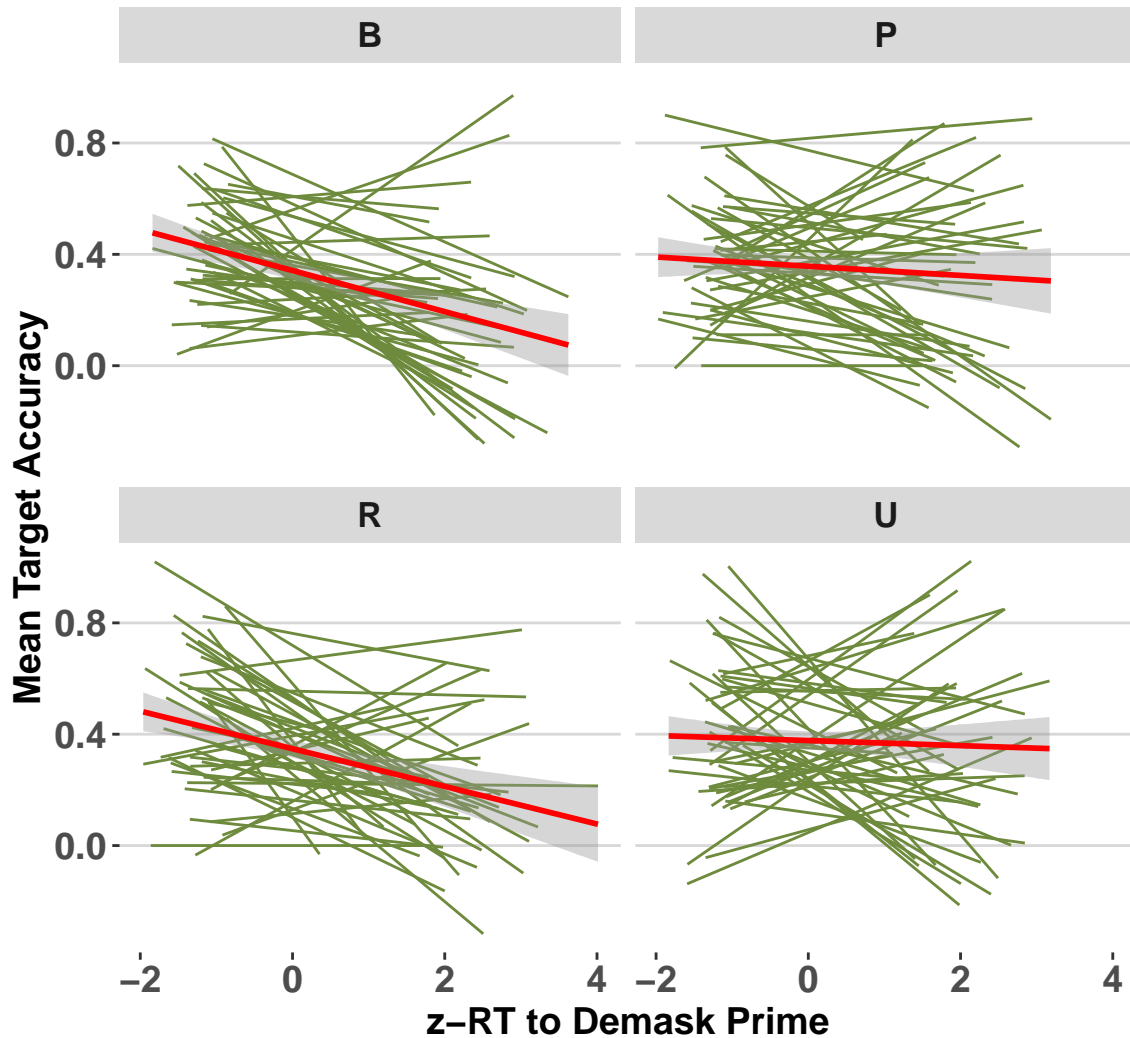
8.3 Model 2: Raw data

```

> primeplot = primewith_final_z %>%
+   mutate(PrimeType = factor(PrimeCondition,
+                               levels = unique(PrimeCondition),
+                               labels = c("Both Prime", "Phonological Prime",
+                                           "Semantic Prime", "Unrelated Prime")))%>%
+   ggplot(aes(x = zPrimeRecogRT_trim, y = Accuracy,
+               group = factor(Subject))) +
+   geom_smooth(method = "lm", se = FALSE, color = "darkolivegreen4", size = 0.5)+
+   facet_wrap(~PrimeCondition)+
+   xlab("z-RT to Demask Prime") + ylab ("Mean Target Accuracy")+
+   ggtitle("YA: Target Retrieval Accuracy by \nPrime Demasking RT & Prime Condition")+
+   theme_hc() +
+   theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+         axis.title = element_text(face = "bold", size = rel(1.2)),
+         legend.title = element_text(face = "bold", size = rel(1.2)),
+         strip.text.x = element_text(face = "bold", size = rel(1.4)),
+         plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
> primeplot + stat_smooth(aes(group = PrimeCondition), method = "lm", color = "red")

```

YA: Target Retrieval Accuracy by Prime Demasking RT & Prime Condition



8.4 Model 2: Raw data: No subject lines

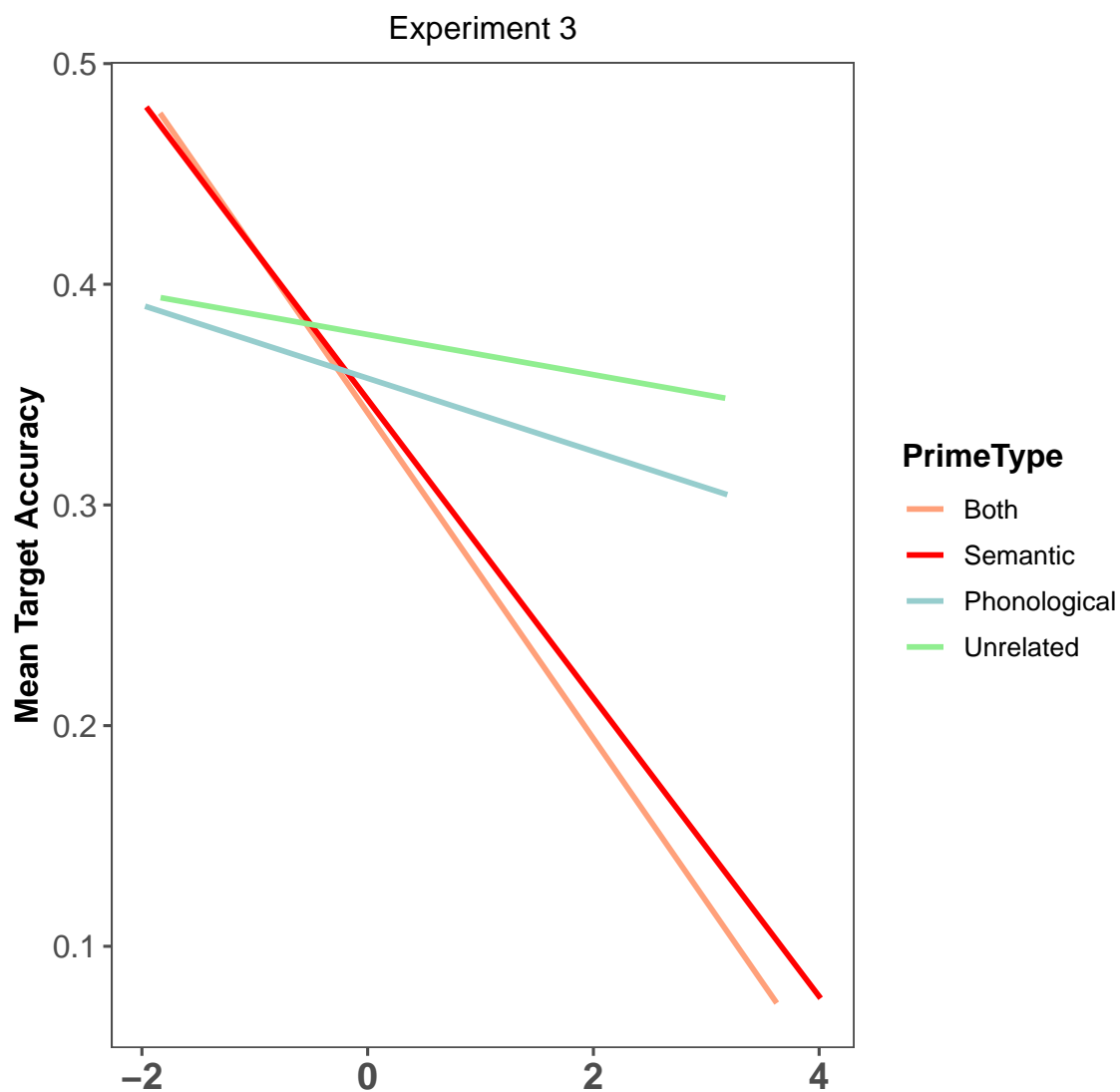
```
> primewith_final_z$primefac = ordered(as.factor(as.character(primewith_final_z$PrimeCon
> primewith_final_z %>%
+   mutate(PrimeType = factor(primefac, levels = unique(primefac),
+                             labels = c("Both","Semantic", "Phonological",
+                             "Unrelated"))))%>%
+   ggplot(aes(x = zPrimeRecogRT_trim, y = Accuracy,
+             group = PrimeType, color = PrimeType)) +
+   geom_smooth(method = "lm", se = FALSE)+
```



```

+   xlab("") + ylab ("Mean Target Accuracy")+
+   ggtitle("Experiment 3")+
+   theme_few() +
+   scale_color_manual(values = c( "lightsalmon", "red",
+                                   "paleturquoise3","lightgreen"))+
+   ggtitle("Experiment 3") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5, size = rel(1)),
+         axis.text.x = element_text(face = "bold", size = rel(1.2)))

```



8.5 RTprimeRTmodel2

```
> # RTprime_RT_model_2 = lmer(data = primewith_final_z,
> #                               zTargetRecogRT_trim ~ zPrimeRecogRT_trim*PrimeCondition +
> #                               (1|Subject) + (1|Stimuli2))
> # summary(RTprime_RT_model_2)
>
> primert_model = lmer(data = primewith_final_z,
+                       zPrimeRecogRT_trim ~ 1 + (1 | Subject) +
+                       (1|Stimuli2))
> summary(primert_model)
```

```
Linear mixed model fit by REML. t-tests use Satterthwaite's method [
lmerModLmerTest]
```

```
Formula: zPrimeRecogRT_trim ~ 1 + (1 | Subject) + (1 | Stimuli2)
Data: primewith_final_z
```

```
REML criterion at convergence: 9341.3
```

```
Scaled residuals:
```

	Min	1Q	Median	3Q	Max
	-2.1121	-0.7343	-0.2065	0.5818	4.1568

```
Random effects:
```

Groups	Name	Variance	Std.Dev.
Stimuli2	(Intercept)	0.06042	0.2458
Subject	(Intercept)	0.00000	0.0000
Residual		0.92097	0.9597

```
Number of obs: 3352, groups: Stimuli2, 72; Subject, 48
```

```
Fixed effects:
```

	Estimate	Std. Error	df	t value	Pr(> t)
(Intercept)	-0.00394	0.03338	70.57723	-0.118	0.906

```
> VarCorr(primert_model)
```

Groups	Name	Std.Dev.
Stimuli2	(Intercept)	0.24580
Subject	(Intercept)	0.00000
Residual		0.95967

```
> SD_prime <- as.data.frame(VarCorr(primert_model))[3, 5]
> ## now we need to find increments for each prime condition
>
> primert_model_2 <- lmer(data = primewith_final_z,
+                          zPrimeRecogRT_trim ~ 1 + PrimeCondition +
+                          (1|Subject) + (1|Stimuli2))
> prime_inc_1_U <- 0*fixef(primert_model_2)[1]
```

```

> prime_Inc_1_B <- 1*fixef(primert_model_2)[2]
> prime_Inc_1_P <- 1*fixef(primert_model_2)[3]
> prime_Inc_1_R <- 1*fixef(primert_model_2)[4]
> predict_data_U <- with(primewith_final_z,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_U-SD_prime,
+ to=-prime_Inc_1_U+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 0))
> predict_data_B <- with(primewith_final_z,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_B-SD_prime,
+ to=-prime_Inc_1_B+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 1))
> predict_data_P <- with(primewith_final_z,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_P-SD_prime,
+ to=-prime_Inc_1_P+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 2))
> predict_data_R <- with(primewith_final_z,
+ data.frame(school=1,
+ zPrimeRecogRT_trim=seq(from=-prime_Inc_1_R-SD_prime,
+ to=-prime_Inc_1_R+SD_prime,
+ by=SD_prime),
+ PrimeCondition = 3))
> predict_data = rbind(predict_data_U,
+ predict_data_B,
+ predict_data_P,
+ predict_data_R)
> predict_data$PrimeCondition = ifelse(predict_data$PrimeCondition == 0, "U",
+ ifelse(predict_data$PrimeCondition == 1, "B",
+ ifelse(predict_data$PrimeCondition == 2, "P", "R")))
> predict_data = predict_data %>%
+ mutate(predicted_values = predict(RTprime_RT_model_2,
+ newdata = predict_data, re.form = NA))
> predict_data$PrimeCondition = ordered(as.factor(as.character(predict_data$PrimeCondition)))
> predict_data %>%
+ mutate(PrimeType = factor(PrimeCondition, levels = unique(PrimeCondition),
+ labels = c("Unrelated",
+ "Both", "Phonological", "Semantic")))%>%
+ ggplot(aes(x = zPrimeRecogRT_trim, y = predicted_values,
+ color = PrimeType)) +
+ geom_line(size = 1) +
+ xlab("z-RT to Demask Prime") + ylab ("z-RT to Demask Target")+
+ ggtitle("Experiment 3")+
+ theme_few() +

```

```

+   scale_color_manual(values = c( "lightgreen", "lightsalmon",
+                                   "paleturquoise3","red"))+
+   theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+         axis.title = element_text(face = "bold", size = rel(1.2)),
+         legend.title = element_text(face = "bold", size = rel(1.2)),
+         plot.title = element_text(face = "bold", size = rel(1.2), hjust = .5))
>

```

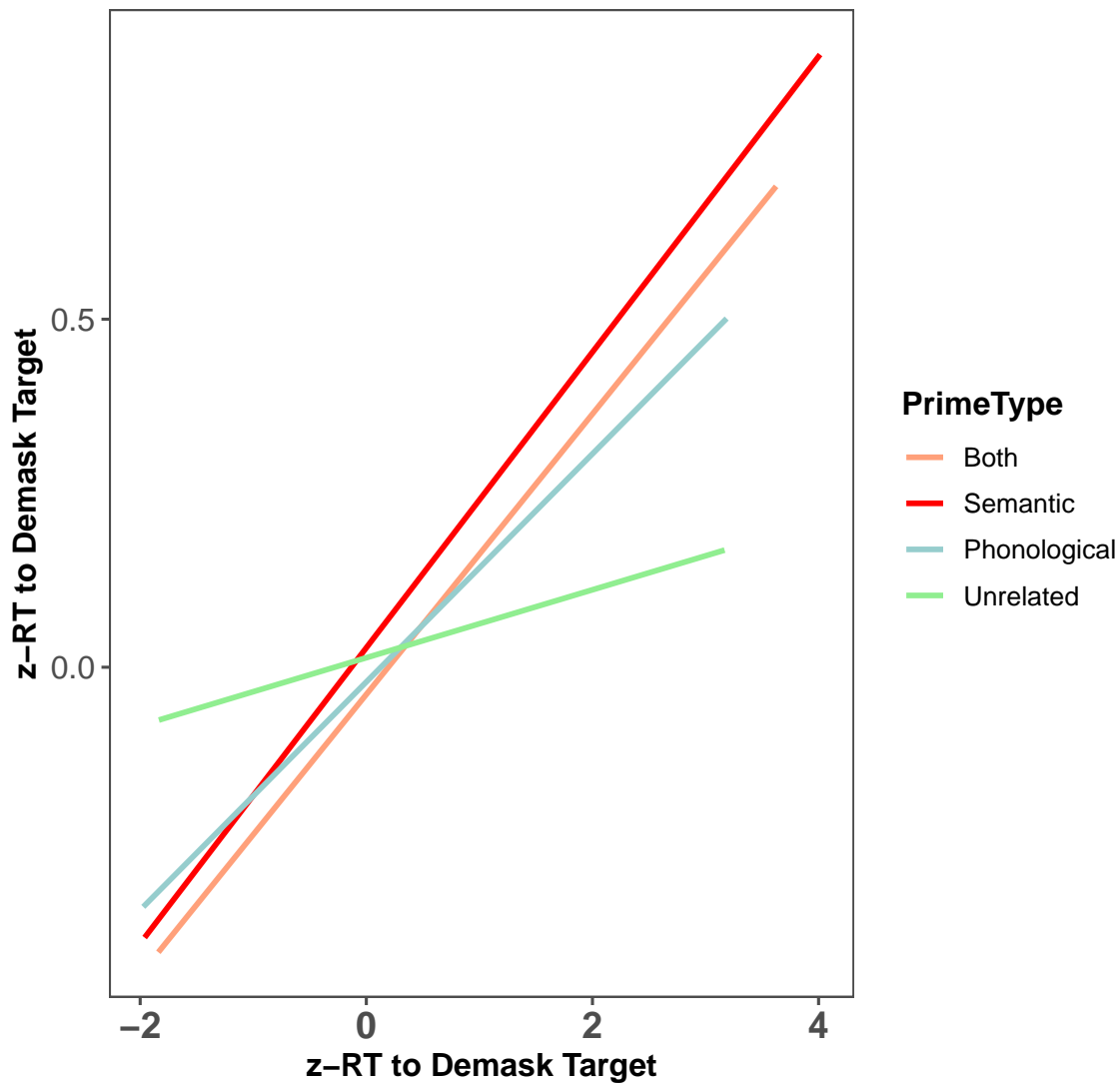
8.6 Target RT Model 2: Raw data: No subject lines

```

> primewith_final_z %>%
+   mutate(PrimeType = factor(primefac, levels = unique(primefac),
+                             labels = c("Both","Semantic", "Phonological",
+                                           "Unrelated")))%>%
+   ggplot(aes(x = zPrimeRecogRT_trim, y = zTargetRecogRT_trim,
+             group = PrimeType, color = PrimeType)) +
+   geom_smooth(method = "lm", se = FALSE, size = 1)+
+   # ylim(-0.5,0.5)+
+   # facet_wrap(~PrimeCondition, nrow = 1)+
+   xlab("z-RT to Demask Target") + ylab ("z-RT to Demask Target")+
+   theme_few() +
+   scale_color_manual(values = c( "lightsalmon", "red",
+                                   "paleturquoise3","lightgreen"))+
+   ggtitle("Experiment 3") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5, size = rel(1)),
+         axis.text.x = element_text(face = "bold", size = rel(1.2)))

```

Experiment 3



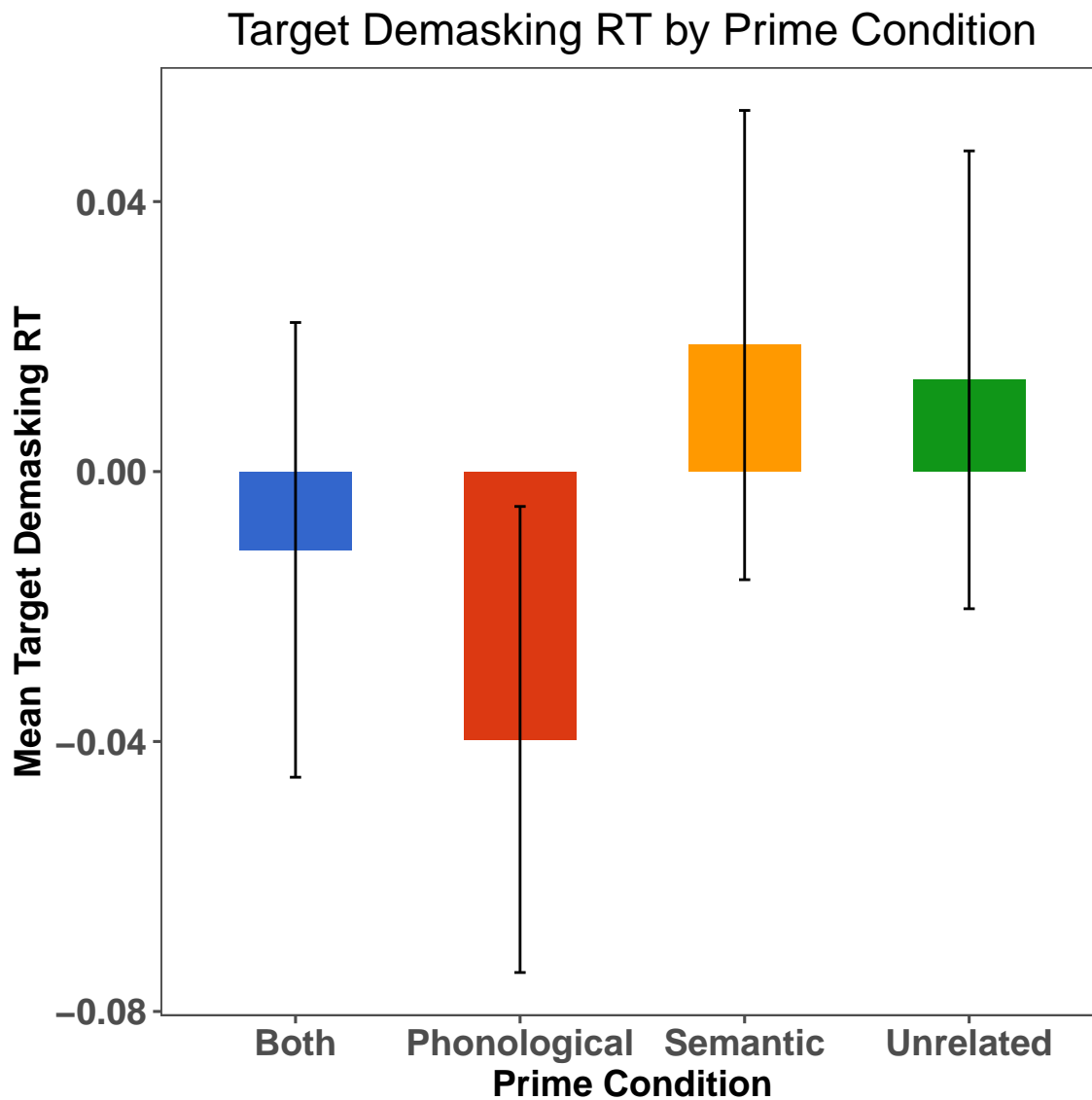
8.7 Target RT Model 1

```
> targetRT_rmisc = Rmisc::summarySE(primewith_final_z,
+                                   measurevar = "zTargetRecogRT_trim",
+                                   groupvars = c("PrimeCondition"))
> library(ggplot2)
> library(ggthemes)
> targetRT_rmisc %>% mutate(`Prime Condition` = factor(PrimeCondition,
+                                                         levels = unique(PrimeCondition),
+                                                         labels = c("Both", "Phonological",
```

```

+           "Semantic", "Unrelated")))) %>%
+ ggplot(aes(x = `Prime Condition`,
+           y = zTargetRecogRT_trim, fill = `Prime Condition`))+
+   geom_bar(stat = "identity", position = "dodge",
+           width = 0.5)+
+   geom_errorbar(aes(ymin = zTargetRecogRT_trim - se, ymax = zTargetRecogRT_trim + se),
+               width=.05, position=position_dodge(.5)) +
+   theme_few()+
+   guides (fill = FALSE)+
+   scale_fill_gdocs()+
+   xlab("Prime Condition") + ylab("Mean Target Demasking RT") +
+   ggtitle("Target Demasking RT by Prime Condition") +
+   theme(axis.text = element_text(face = "bold", size = rel(1.2)),
+         axis.title = element_text(face = "bold", size = rel(1.2)),
+         legend.title = element_text(face = "bold", size = rel(1.2)),
+         plot.title = element_text( size = rel(1.4), hjust = .5))

```



9 MTurk Covariate Analyses

```
> itemratings= read.csv("Abhilasha_item_wide.csv",  
+                       header = TRUE, sep = ",")  
> main = PrimeRetrieval  
> main = main %>% filter(PrimeCondition %in% c("P", "R"))  
> main_item = merge(main, itemratings,  
+                   by = c("Stimuli2", "PrimeCondition"))  
> main_item = dplyr::arrange(main_item, ID, Stimuli2, PrimeType)  
> ## Impacting Ret/NotRet
```

```

>
> main_item$PrimeFirstResp_ACC = as.factor(main_item$PrimeFirstResp_ACC)
> m_young_prime2 = lme4::glmer(data = main_item, Accuracy ~
+       PrimeFirstResp_ACC*PrimeCondition + PrimeAcc +
+       MeaningRating +
+       (1|Subject) + (1|Stimuli2),
+       family = "binomial",
+       control=glmerControl(optimizer="bobyqa",
+       optCtrl=list(maxfun=100000)))
> summary(m_young_prime2)

```

```

Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial (logit)
Formula:
Accuracy ~ PrimeFirstResp_ACC * PrimeCondition + PrimeAcc + MeaningRating +
(1 | Subject) + (1 | Stimuli2)
Data: main_item
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))

```

AIC	BIC	logLik	deviance	df.resid
1915.4	1959.0	-949.7	1899.4	1720

Scaled residuals:

Min	1Q	Median	3Q	Max
-3.2423	-0.5983	-0.3353	0.6753	3.2464

Random effects:

Groups	Name	Variance	Std.Dev.
Stimuli2	(Intercept)	1.4808	1.2169
Subject	(Intercept)	0.4796	0.6926

Number of obs: 1728, groups: Stimuli2, 72; Subject, 48

Fixed effects:

	Estimate	Std. Error	z value	Pr(> z)
(Intercept)	-0.869161	0.403129	-2.156	0.0311 *
PrimeFirstResp_ACC1	-0.232409	0.080057	-2.903	0.0037 **
PrimeCondition1	-0.002185	0.168317	-0.013	0.9896
PrimeAcc	0.119265	0.301918	0.395	0.6928
MeaningRating	-0.014424	0.092324	-0.156	0.8759
PrimeFirstResp_ACC1:PrimeCondition1	0.142212	0.066209	2.148	0.0317 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:

	(Intr)	PrFR_ACC1	PrmCn1	PrmAcc	MnngRt
PrmFrR_ACC1	-0.200				
PrimeCndtn1	-0.724	0.000			


```
PrimeAcc      -0.411  0.537   -0.028
MeaningRtnng -0.801  0.008    0.933  0.039
PFR_ACC1:PC   0.090  0.002   -0.058  0.009 -0.101
```

```
> options(contrasts = c("contr.sum", "contr.poly"))
> car::Anova(m_young_prime2)
```

Analysis of Deviance Table (Type II Wald chisquare tests)

Response: Accuracy

	Chisq	Df	Pr(>Chisq)
PrimeFirstResp_ACC	8.4552	1	0.00364 **
PrimeCondition	0.0125	1	0.91103
PrimeAcc	0.1560	1	0.69282
MeaningRating	0.0244	1	0.87585
PrimeFirstResp_ACC:PrimeCondition	4.6135	1	0.03172 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

```
> anova(m_young_prime2)
```

Analysis of Variance Table

	Df	Sum Sq	Mean Sq	F value
PrimeFirstResp_ACC	1	14.2595	14.2595	14.2595
PrimeCondition	1	0.0429	0.0429	0.0429
PrimeAcc	1	0.1428	0.1428	0.1428
MeaningRating	1	0.0047	0.0047	0.0047
PrimeFirstResp_ACC:PrimeCondition	1	4.6981	4.6981	4.6981

```
> #sjPlot::plot_model(m_young_prime2, type = "int")
```

10 Response Analysis

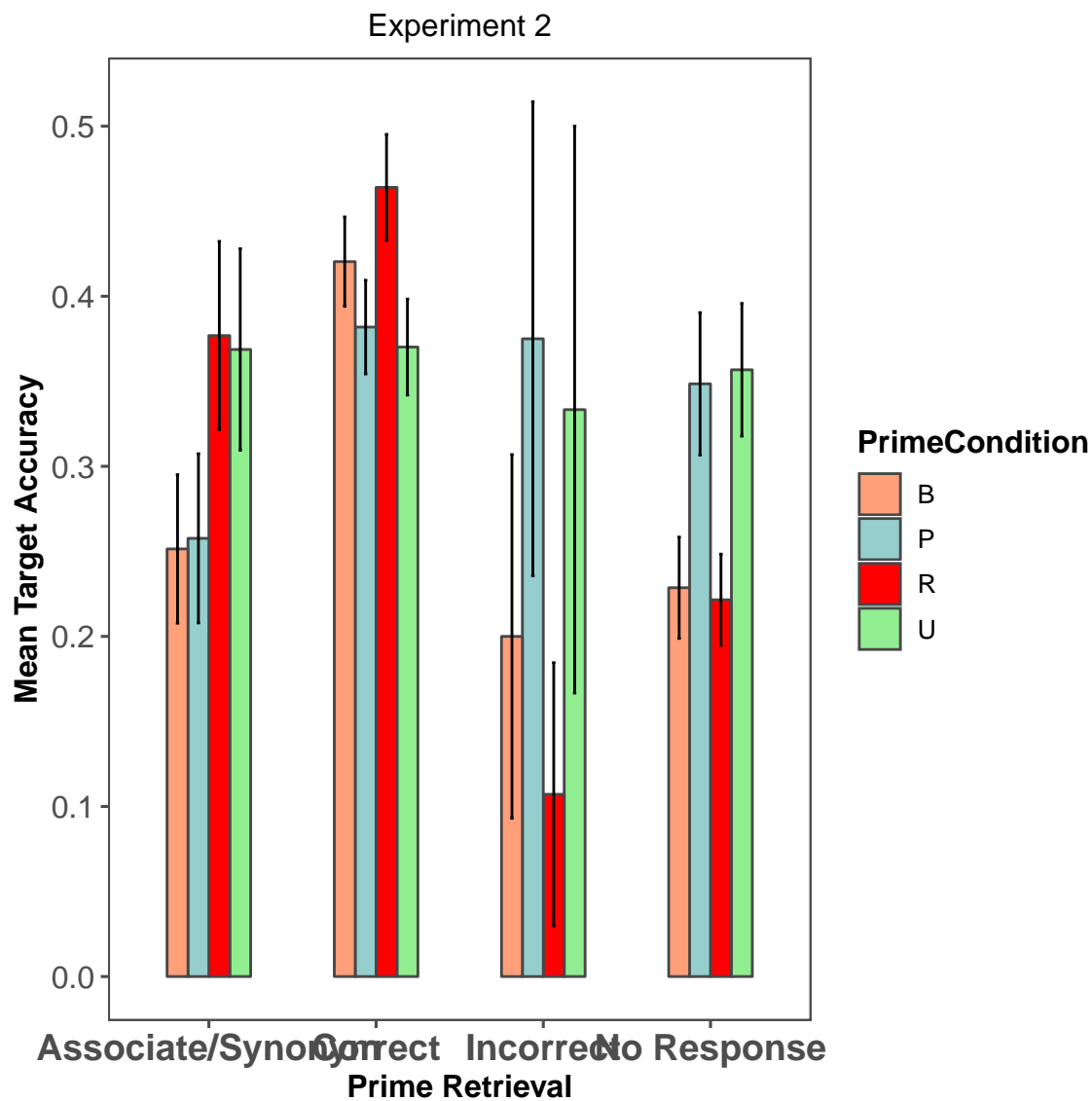
10.1 All Responses

```
> E3_YA = read.csv("E3_YA_Responses.csv",
+                 header = TRUE, sep = ",")
> E3_YA$AllResponse = ifelse(E3_YA$PrimeRespType %in%
+                             c("Associate", "Synonym"), "Associate/Synonym",
+                             ifelse(E3_YA$PrimeRespType == "NoResponse",
+                                     "No Response",
+                                     ifelse(E3_YA$PrimeRespType == "Correct", "Correct",
+                                             "Incorrect"))))
> E3_YA_subject = group_by(E3_YA, Subject, PrimeCondition, AllResponse) %>%
+   summarize_at(vars(Accuracy), mean)
> ret_figure = Rmisc::summarySE(E3_YA_subject,
```

```

+           measurevar = "Accuracy",
+           groupvars = c("PrimeCondition", "AllResponse"))
> library(ggplot2)
> library(ggthemes)
> library(dplyr)
> ret_figure %>%
+   ggplot(aes(x = AllResponse, y = Accuracy,
+             group = PrimeCondition,
+             fill = PrimeCondition)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.5,
+           color = "gray28") +
+   geom_errorbar(aes(ymin = Accuracy - se,
+                     ymax = Accuracy + se),
+                 width=.08, position=position_dodge(.5)) +
+   theme_few() +
+   # scale_fill_manual(values = c("lightsalmon", "paleturquoise3",
+   #                               "red", "lightgreen")) +
+   xlab("Prime Retrieval") + ylab("Mean Target Accuracy") +
+   ggtitle("Experiment 2") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5, size = rel(1)),
+         axis.text.x = element_text(face = "bold", size = rel(1.2)))

```



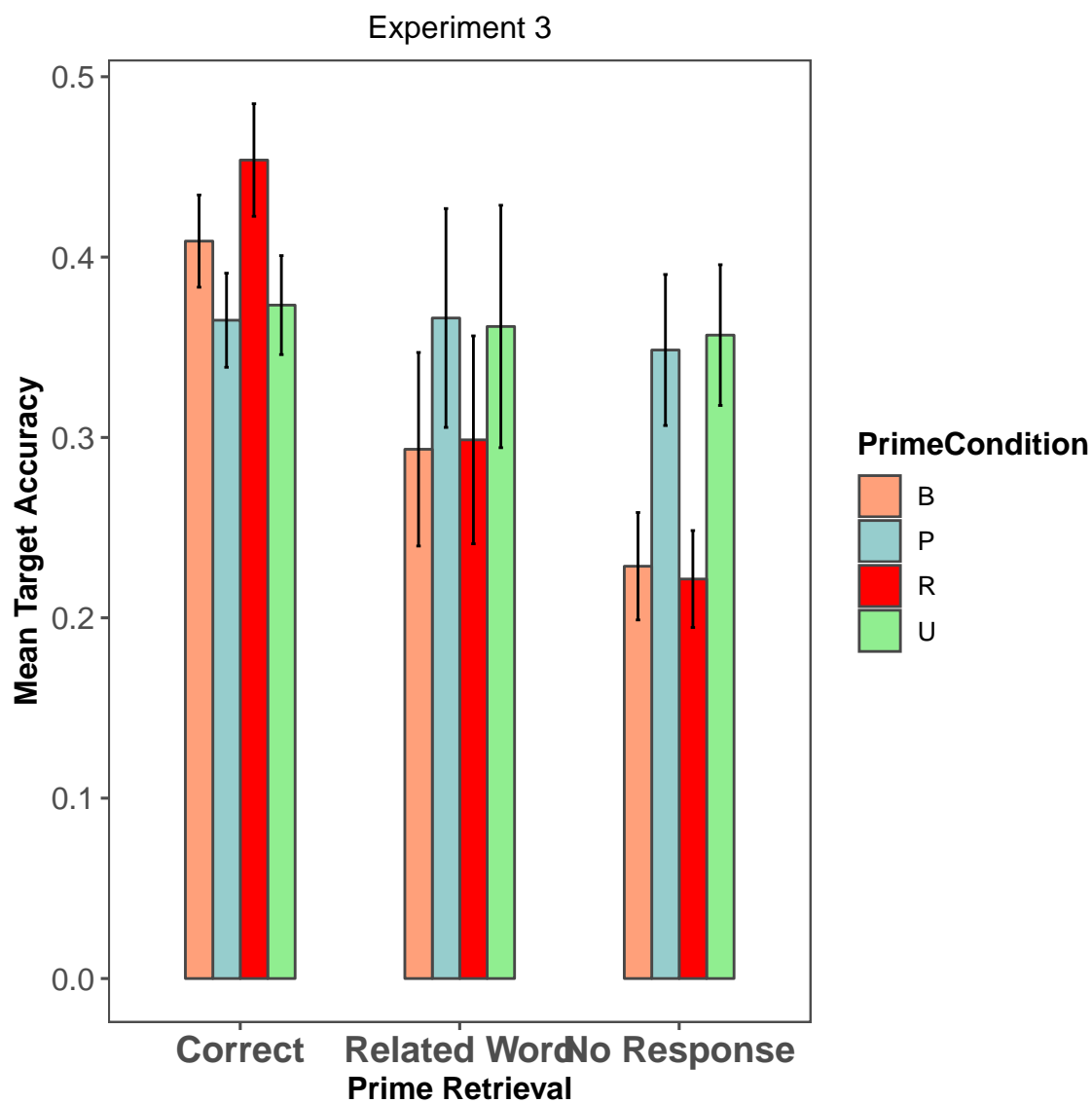
10.2 3-group Responses

```
> E3_YA = read.csv("E3_YA_Responses.csv",
+                 header = TRUE, sep = ",")
> E3_YA$Response = ifelse(E3_YA$PrimeRespType %in%
+                 c("Associate", "Incorrect"), "Related Word",
+                 ifelse(E3_YA$PrimeRespType == "NoResponse",
+                 "No Response", "Correct"))
> E3_YA$Response = ordered(as.factor(as.character(E3_YA$Response)),
+                 levels = c("Correct", "Related Word", "No Response"))
```

```

> E3_YA_subject = group_by(E3_YA, Subject, PrimeCondition, Response) %>%
+   summarize_at(vars(Accuracy), mean)
> ret_figure = Rmisc::summarySE(E3_YA_subject,
+                               measurevar = "Accuracy",
+                               groupvars = c("PrimeCondition", "Response"))
> library(ggplot2)
> library(ggthemes)
> library(dplyr)
> ret_figure %>%
+   ggplot(aes(x = Response, y = Accuracy,
+              group = PrimeCondition,
+              fill = PrimeCondition)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.5,
+            color = "gray28") +
+   geom_errorbar(aes(ymin = Accuracy - se,
+                     ymax = Accuracy + se),
+                 width=.08, position=position_dodge(.5)) +
+   theme_few() +
+   # scale_fill_canvas() +
+   scale_fill_manual(values = c("lightsalmon", "paleturquoise3",
+                                "red", "lightgreen")) +
+   xlab("Prime Retrieval") + ylab("Mean Target Accuracy") +
+   ggtitle("Experiment 3") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5, size = rel(1)),
+         axis.text.x = element_text(face = "bold", size = rel(1.2)))

```



10.3 POS-split Responses

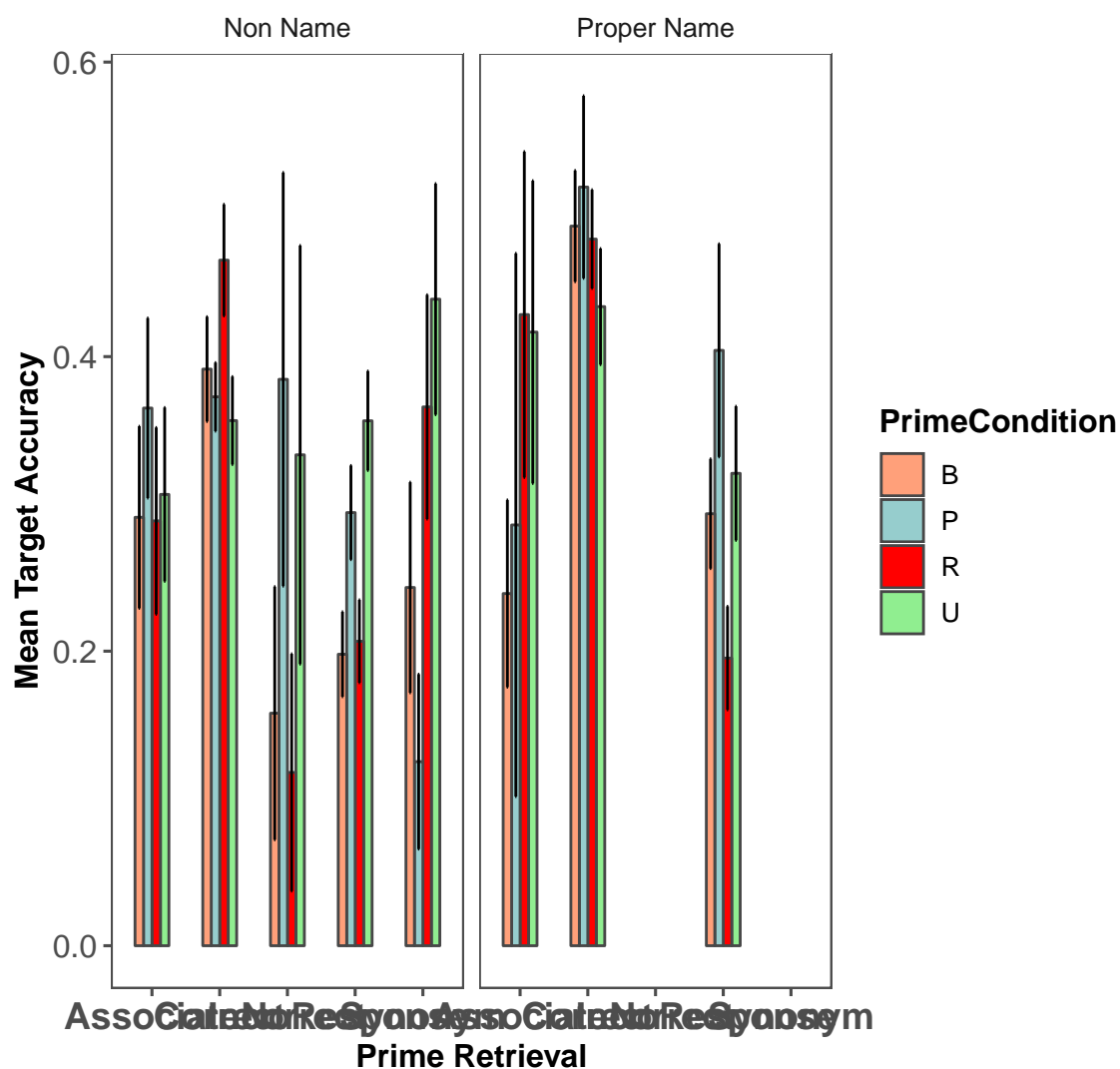
```
> ret_figure = Rmisc::summarySE(E3_YA,
+                               measurevar = "Accuracy",
+                               groupvars = c("Prime_POS", "PrimeCondition", "PrimeRespType"))
> library(ggplot2)
> library(ggthemes)
> library(dplyr)
> ret_figure %>%
+   ggplot(aes(x = PrimeRespType, y = Accuracy,
```

```

+           group =PrimeCondition ,
+           fill = PrimeCondition)) +
+   geom_bar(stat = "identity", position = "dodge", width = 0.5,
+           color = "gray28")+
+   geom_errorbar(aes(ymin = Accuracy - se,
+                     ymax = Accuracy + se),
+                 width=.08, position=position_dodge(.5)) +
+   theme_few()+
+ facet_wrap(~Prime_POS)+
+   scale_fill_manual(values = c( "lightsalmon","paleturquoise3",
+                                "red", "lightgreen"))+
+   xlab("Prime Retrieval") + ylab("Mean Target Accuracy") +
+   ggtitle("E2") +
+   theme(axis.text = element_text(size = rel(1)),
+         axis.title = element_text(face = "bold", size = rel(1)),
+         legend.title = element_text(face = "bold", size = rel(1)),
+         plot.title = element_text(hjust = .5, size = rel(1)),
+         axis.text.x = element_text(face = "bold", size = rel(1.2)))

```

E2



10.4 LME

```
> E3_YA$Response = as.factor(E3_YA$Response)
> contrasts(E3_YA$Response) = contr.treatment(3, base = 1)
> contrasts(E3_YA$PrimeCondition) = contr.treatment(4, base = 4)
> # E3_YA$Relationship = ifelse(E3_YA$PrimeCondition %in% c("B", "P"), "Unrelated",
> #                             "Related")
> #
> # E3_YA$Relationship = as.factor(E3_YA$Relationship)
> # contrasts(E3_YA$Relationship) = contr.treatment(2, base = 2)
```

```

>
> TOTFeedback_hlm2 = glmer(data = E3_YA,
+                           Accuracy ~ PrimeCondition*Response +
+                           (1|Subject) + (1|Stimuli2), family = "binomial",
+                           control=glmerControl(optimizer="bobyqa",
+                           optCtrl=list(maxfun=100000)))
> summary(TOTFeedback_hlm2)

```

```

Generalized linear mixed model fit by maximum likelihood (Laplace
Approximation) [glmerMod]
Family: binomial ( logit )
Formula: Accuracy ~ PrimeCondition * Response + (1 | Subject) + (1 | Stimuli2)
Data: E3_YA
Control: glmerControl(optimizer = "bobyqa", optCtrl = list(maxfun = 1e+05))

      AIC      BIC   logLik deviance df.resid
3631.4   3717.4  -1801.7   3603.4     3442

Scaled residuals:
    Min       1Q   Median       3Q      Max
-3.1100 -0.5755 -0.3081  0.6292  5.5292

Random effects:
 Groups   Name      Variance Std.Dev.
Stimuli2 (Intercept) 1.8043   1.3432
Subject  (Intercept) 0.4739   0.6884
Number of obs: 3456, groups: Stimuli2, 72; Subject, 48

Fixed effects:
              Estimate Std. Error z value Pr(>|z|)
(Intercept)    -0.71061    0.22106  -3.215  0.00131 **
PrimeCondition1 -0.06505    0.16804  -0.387  0.69865
PrimeCondition2 -0.16015    0.15944  -1.004  0.31516
PrimeCondition3  0.03629    0.16480   0.220  0.82571
Response2       -0.07667    0.27805  -0.276  0.78275
Response3       -0.12719    0.18650  -0.682  0.49526
PrimeCondition1:Response2 -0.33413    0.39133  -0.854  0.39320
PrimeCondition2:Response2  0.25382    0.40774   0.623  0.53361
PrimeCondition3:Response2 -0.18625    0.41057  -0.454  0.65009
PrimeCondition1:Response3 -0.41870    0.27227  -1.538  0.12409
PrimeCondition2:Response3  0.18800    0.27301   0.689  0.49107
PrimeCondition3:Response3 -0.52886    0.27096  -1.952  0.05096 .
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Correlation of Fixed Effects:
      (Intr) PrmCn1 PrmCn2 PrmCn3 Rspns2 Rspns3 PC1:R2 PC2:R2 PC3:R2
PrimeCndtn1 -0.360

```



```

PrimeCndtn2 -0.382  0.514
PrimeCndtn3 -0.365  0.492  0.518
Response2   -0.222  0.295  0.305  0.296
Response3   -0.340  0.446  0.472  0.450  0.263
PrmCndt1:R2  0.159 -0.447 -0.228 -0.217 -0.713 -0.198
PrmCndt2:R2  0.150 -0.212 -0.400 -0.206 -0.677 -0.182  0.494
PrmCndt3:R2  0.147 -0.204 -0.211 -0.418 -0.675 -0.177  0.484  0.462
PrmCndt1:R3  0.227 -0.645 -0.330 -0.312 -0.183 -0.677  0.288  0.137  0.127
PrmCndt2:R3  0.231 -0.316 -0.618 -0.314 -0.176 -0.684  0.140  0.244  0.124
PrmCndt3:R3  0.227 -0.308 -0.326 -0.632 -0.180 -0.676  0.136  0.128  0.264
          PC1:R3 PC2:R3
PrimeCndtn1
PrimeCndtn2
PrimeCndtn3
Response2
Response3
PrmCndt1:R2
PrmCndt2:R2
PrmCndt3:R2
PrmCndt1:R3
PrmCndt2:R3  0.476
PrmCndt3:R3  0.465  0.471

```

```

> sjPlot::plot_model(TOTFeedback_hlm2, type = "int")
> car::Anova(TOTFeedback_hlm2)

```

Analysis of Deviance Table (Type II Wald chisquare tests)

Response: Accuracy

	Chisq	Df	Pr(>Chisq)
PrimeCondition	4.7464	3	0.191334
Response	9.4662	2	0.008799 **
PrimeCondition:Response	9.9930	6	0.124946

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

10.5 Specific Comparisons

```

> ## correct responses
> responses_correct = E3_YA %>% filter(Response == "Correct")
> responses_correct_sub = group_by(responses_correct, Subject, PrimeCondition) %>%
+   summarise_at(vars(Accuracy), mean)
> responses_correct_wide = spread(responses_correct_sub, PrimeCondition, Accuracy)
> t.test(responses_correct_wide$R, responses_correct_wide$U,
+   paired = TRUE)

```

Paired t-test

```
data: responses_correct_wide$R and responses_correct_wide$U
t = 2.116, df = 47, p-value = 0.03967
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 0.003963509 0.156902708
sample estimates:
mean of the differences
      0.08043311
```

```
> ## other responses
> responses_other = E3_YA %>% filter(Response == "Related Word")
> responses_other_sub = group_by(responses_other, Subject, PrimeCondition) %>%
+   summarise_at(vars(Accuracy), mean)
> responses_other_wide = spread(responses_other_sub, PrimeCondition, Accuracy)
> t.test(responses_other_wide$R, responses_other_wide$U,
+   paired = TRUE)
```

Paired t-test

```
data: responses_other_wide$R and responses_other_wide$U
t = -0.36576, df = 31, p-value = 0.717
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.2055052  0.1430052
sample estimates:
mean of the differences
      -0.03125
```

```
> t.test(responses_other_wide$B, responses_other_wide$U,
+   paired = TRUE)
```

Paired t-test

```
data: responses_other_wide$B and responses_other_wide$U
t = -1.1901, df = 34, p-value = 0.2423
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.26928897  0.07037741
sample estimates:
mean of the differences
      -0.09945578
```

```
> t.test(responses_other_wide$P, responses_other_wide$U,
+   paired = TRUE)
```

Paired t-test

```
data: responses_other_wide$P and responses_other_wide$U
t = 0.32673, df = 31, p-value = 0.7461
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.1392471  0.1923721
sample estimates:
mean of the differences
      0.0265625
```

```
> responses_none = E3_YA %>% filter(Response == "No Response")
> ## no response
> responses_none_sub = group_by(responses_none, Subject, PrimeCondition) %>%
+   summarise_at(vars(Accuracy), mean)
> responses_none_wide = spread(responses_none_sub, PrimeCondition, Accuracy)
> t.test(responses_none_wide$R, responses_none_wide$U,
+   paired = TRUE)
```

Paired t-test

```
data: responses_none_wide$R and responses_none_wide$U
t = -3.51, df = 45, p-value = 0.001031
alternative hypothesis: true difference in means is not equal to 0
95 percent confidence interval:
 -0.19467697 -0.05271802
sample estimates:
mean of the differences
      -0.1236975
```