

SLT_paper

AC

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Contents

History:	1
Read data in	1
Correspondence between lab & zooniverse annotation at the level of segments	1
Precision	5
Recall	6
Child level descriptors	6

History:

- 2020-08-05 final first version

Read data in

```
# read dataset composed with python
data_all <- read.csv("final_classifications_PU_zoon.csv")

#remove the word mixed that takes up space and is unnecessary
data_all$Zoon_classif=factor(gsub("Mixed_", "", as.character(data_all$Zoon_classif), fixed=T))

#relevel the factor so that it's easier to read
data_all$Zoon_classif=factor(data_all$Zoon_classif, levels=c("Canonical", "Non-Canonical",
                                                            "Crying", "Laughing", "Junk", levels(data_all$Zoon_classif)))

# create lab column with easier to read correspondance
data_all$lab<-as.character(data_all$Major_Choice)
data_all$lab[data_all$lab=="Non-canonical syllables"]<-"Non-Canonical"
data_all$lab[data_all$lab=="Canonical syllables"]<-"Canonical"
data_all$lab[data_all$lab %in% c("Don't mark", "None")]<-"Junk"
data_all$lab=factor(data_all$lab, levels=levels(data_all$Zoon_classif))
#apply same factor levels as zooniverse so that we can do symmetrical confusion matrices
```

Correspondence between lab & zooniverse annotation at the level of segments

Here we look at to what extent zooniverse and lab annotations match at the level of individual segments. Each data point is one segment (one “vocalization”).

```
table(data_all$lab)
```

```
##
##           Canonical           Non-Canonical
##           258             2532
##           Crying             Laughing
##           51              49
##           Junk             Laughing_Canonical
##           904              0
##           Laughing_Crying   Laughing_Non-Canonical
##           0                0
## Laughing_Non-Canonical_Crying   Non-Canonical_Crying
##           0                0
## Non-Canonical_Laughing_Crying
##           0
```

```
table(data_all$Zoon_classif)
```

```
##
##           Canonical           Non-Canonical
##           226             2535
##           Crying             Laughing
##           94              130
##           Junk             Laughing_Canonical
##           625              2
##           Laughing_Crying   Laughing_Non-Canonical
##           3                76
## Laughing_Non-Canonical_Crying   Non-Canonical_Crying
##           3                99
## Non-Canonical_Laughing_Crying
##           1
```

```
mycf=confusionMatrix(data_all$lab, data_all$Zoon_classif, dnn = c("Lab","Zooniverse"))
```

```
conf_tab=mycf$table
```

```
# this package uses sensitivity & specificity
#Sensitivity=recall
#Specificity=precision
```

```
mycf
```

```
## Confusion Matrix and Statistics
```

```
##
##           Zooniverse
## Lab Canonical Non-Canonical Crying Laughing Junk
## Canonical          93          122          3          8          22
## Non-Canonical       51          2057         60          49         193
## Crying              0           17          13           2           4
## Laughing            0           5           2          26           6
## Junk               82          334          16          45         400
## Laughing_Canonical  0           0           0           0           0
## Laughing_Crying     0           0           0           0           0
## Laughing_Non-Canonical 0           0           0           0           0
## Laughing_Non-Canonical_Crying 0           0           0           0           0
```

##	Non-Canonical_Crying	0	0	0	0	0
##	Non-Canonical_Laughing_Crying	0	0	0	0	0
##		Zooniverse				
##	Lab		Laughing_Canonical	Laughing_Crying		
##	Canonical		0	1		
##	Non-Canonical		0	1		
##	Crying		0	1		
##	Laughing		1	0		
##	Junk		1	0		
##	Laughing_Canonical		0	0		
##	Laughing_Crying		0	0		
##	Laughing_Non-Canonical		0	0		
##	Laughing_Non-Canonical_Crying		0	0		
##	Non-Canonical_Crying		0	0		
##	Non-Canonical_Laughing_Crying		0	0		
##		Zooniverse				
##	Lab		Laughing_Non-Canonical			
##	Canonical		6			
##	Non-Canonical		51			
##	Crying		0			
##	Laughing		8			
##	Junk		11			
##	Laughing_Canonical		0			
##	Laughing_Crying		0			
##	Laughing_Non-Canonical		0			
##	Laughing_Non-Canonical_Crying		0			
##	Non-Canonical_Crying		0			
##	Non-Canonical_Laughing_Crying		0			
##		Zooniverse				
##	Lab		Laughing_Non-Canonical_Crying			
##	Canonical		0			
##	Non-Canonical		1			
##	Crying		1			
##	Laughing		0			
##	Junk		1			
##	Laughing_Canonical		0			
##	Laughing_Crying		0			
##	Laughing_Non-Canonical		0			
##	Laughing_Non-Canonical_Crying		0			
##	Non-Canonical_Crying		0			
##	Non-Canonical_Laughing_Crying		0			
##		Zooniverse				
##	Lab		Non-Canonical_Crying			
##	Canonical		3			
##	Non-Canonical		69			
##	Crying		13			
##	Laughing		0			
##	Junk		14			
##	Laughing_Canonical		0			
##	Laughing_Crying		0			
##	Laughing_Non-Canonical		0			
##	Laughing_Non-Canonical_Crying		0			
##	Non-Canonical_Crying		0			
##	Non-Canonical_Laughing_Crying		0			

```

##                                Zooniverse
## Lab                            Non-Canonical_Laughing_Crying
## Canonical                      0
## Non-Canonical                  0
## Crying                        0
## Laughing                      1
## Junk                          0
## Laughing_Canonical            0
## Laughing_Crying               0
## Laughing_Non-Canonical        0
## Laughing_Non-Canonical_Crying 0
## Non-Canonical_Crying          0
## Non-Canonical_Laughing_Crying 0
##
## Overall Statistics
##
## Accuracy : 0.6824
## 95% CI : (0.6673, 0.6972)
## No Information Rate : 0.6682
## P-Value [Acc > NIR] : 0.0322
##
## Kappa : 0.3773
##
## McNemar's Test P-Value : NA
##
## Statistics by Class:
##
## Class: Canonical Class: Non-Canonical Class: Crying
## Sensitivity      0.41150      0.8114      0.138298
## Specificity      0.95376      0.6227      0.989730
## Pos Pred Value   0.36047      0.8124      0.254902
## Neg Pred Value   0.96239      0.6212      0.978360
## Prevalence       0.05957      0.6682      0.024776
## Detection Rate   0.02451      0.5422      0.003426
## Detection Prevalence 0.06800      0.6674      0.013442
## Balanced Accuracy 0.68263      0.7171      0.564014
##
## Class: Laughing Class: Junk Class: Laughing_Canonical
## Sensitivity      0.200000      0.6400      0.000000
## Specificity      0.993723      0.8410      1.000000
## Pos Pred Value   0.530612      0.4425      NaN
## Neg Pred Value   0.972230      0.9221      0.9994729
## Prevalence       0.034265      0.1647      0.0005271
## Detection Rate   0.006853      0.1054      0.0000000
## Detection Prevalence 0.012915      0.2383      0.0000000
## Balanced Accuracy 0.596861      0.7405      0.5000000
##
## Class: Laughing_Crying Class: Laughing_Non-Canonical
## Sensitivity      0.000000      0.00000
## Specificity      1.000000      1.00000
## Pos Pred Value   NaN          NaN
## Neg Pred Value   0.9992093      0.97997
## Prevalence       0.0007907      0.02003
## Detection Rate   0.0000000      0.00000
## Detection Prevalence 0.0000000      0.00000
## Balanced Accuracy 0.5000000      0.50000

```

```
##                               Class: Laughing_Non-Canonical_Crying
## Sensitivity                   0.0000000
## Specificity                   1.0000000
## Pos Pred Value                NaN
## Neg Pred Value                0.9992093
## Prevalence                    0.0007907
## Detection Rate                0.0000000
## Detection Prevalence          0.0000000
## Balanced Accuracy             0.5000000
##                               Class: Non-Canonical_Crying
## Sensitivity                   0.00000
## Specificity                   1.00000
## Pos Pred Value                NaN
## Neg Pred Value                0.97391
## Prevalence                    0.02609
## Detection Rate                0.00000
## Detection Prevalence          0.00000
## Balanced Accuracy             0.50000
##                               Class: Non-Canonical_Laughing_Crying
## Sensitivity                   0.0000000
## Specificity                   1.0000000
## Pos Pred Value                NaN
## Neg Pred Value                0.9997364
## Prevalence                    0.0002636
## Detection Rate                0.0000000
## Detection Prevalence          0.0000000
## Balanced Accuracy             0.5000000
```

Precision

Precision means: If a segment was called X by zooniverse coders, what proportion of the time was it called X by lab coders?

```
pdf("precision_with_mixed.pdf",height=10,width=10)
prop_cat=data.frame(conf_tab/colSums(conf_tab)*100) #generates precision because columns
prop_cat$id=paste(prop_cat$Lab,prop_cat$Zooniverse)
colnames(prop_cat)[3]<-"pr"

data.frame(conf_tab)->stall
stall$id=paste(stall$Lab,stall$Zooniverse)
stall=merge(stall,prop_cat[c("id","pr")])

ggplot(data = stall, mapping = aes(y = Lab, x=Zooniverse)) +
  geom_tile(aes(fill= rescale(pr)), colour = "white") +
  geom_text(aes(label = paste(round(pr,"%")), vjust = -1,size=2) +
  geom_text(aes(label = Freq), vjust = 1,size=2) +
  scale_fill_gradient(low = "white", high = "red", name = "Percentage") +
  theme(legend.position = "none") +
  xlab("Zooniverse") + ylab("Lab") +
  ggtitle("Precision")+ theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))
dev.off()
```

```
## pdf
## 2
```

Recall

Recall means: If a segment was called X by lab coders, what proportion of the time was it called X by zooniverse coders?

```
pdf("recall_with_mixed.pdf",height=10,width=10)
prop_cat=data.frame(conf_tab/rowSums(conf_tab)*100) #generates recall because rows
prop_cat$id=paste(prop_cat$Lab,prop_cat$Zooniverse)
colnames(prop_cat)[3]<-"rec"

data.frame(conf_tab)->stall
stall$id=paste(stall$Lab,stall$Zooniverse)
stall=merge(stall,prop_cat[c("id","rec")])

ggplot(data = stall, mapping = aes(y = Lab, x=Zooniverse)) +
  geom_tile(aes(fill= rescale(rec)), colour = "white") +
  geom_text(aes(label = paste(round(rec),"%")), vjust = -1,size=2) +
  geom_text(aes(label = Freq), vjust = 1,size=2) +
  scale_fill_gradient(low = "white", high = "red", name = "Percentage") +
  theme(legend.position = "none") +
  xlab("Zooniverse") + ylab("Lab") +
  ggtitle("Recall")+ theme(axis.text.x = element_text(angle = 90, vjust = 0.5, hjust=1))

dev.off()
```

```
## pdf
## 2
```

Child level descriptors

Although there may be errors at the level of the segment, what we really care about is whether Zooniverse annotations give a reliable image of the child's individual development. This is what we look at in this section.

```
#given results above, we map the mixed
data_all$Zoon_classif[data_all$Zoon_classif=="Laughing_Canonical"]<-"Canonical"
data_all$Zoon_classif[data_all$Zoon_classif=="Laughing_Non-Canonical"]<-"Non-Canonical"
data_all$Zoon_classif[data_all$Zoon_classif=="Laughing_Non-Canonical_Crying"]<-"Non-Canonical"
data_all$Zoon_classif[data_all$Zoon_classif=="Laughing_Crying"]<-"Crying"
data_all$Zoon_classif[data_all$Zoon_classif=="Non-Canonical_Crying"]<-"Non-Canonical"
data_all$Zoon_classif[data_all$Zoon_classif=="Non-Canonical_Laughing_Crying"]<-"Non-Canonical"

#and reset the factors for cleanliness
data_all$Zoon_classif=factor(data_all$Zoon_classif)
data_all$lab=factor(data_all$lab)

#get the ns by child, then calculate the linguistic ratio & canonical ratio, separately for zooniverse
ztab=table(data_all$ChildID,data_all$Zoon_classif)
z_lr=rowSums(ztab[,c("Canonical","Non-Canonical")])/rowSums(ztab[,~which(colnames(ztab) %in% c("Junk"))])
z_cr=ztab[,c("Canonical")]/rowSums(ztab[,c("Canonical","Non-Canonical")])
```

```

ltab=table(data_all$ChildID,data_all$lab)
l_lr=rowSums(ltab[,c("Canonical","Non-Canonical")])/rowSums(ltab[,~which(colnames(ztab) %in% c("Junk"))])
l_cr=ltab[,c("Canonical")]/rowSums(ltab[,c("Canonical","Non-Canonical")])

#put all the ratios together
if(sum(rownames(ztab)==rownames(ltab))==dim(ztab)[1]) ratios=cbind(rownames(ztab),z_lr,z_cr,l_lr,l_cr)
colnames(ratios)[1]<-"ChildID"

#add age
ages=aggregate(data_all$Age,by=list(data_all$ChildID),mean) #this is a weird way of adding ages, since

merge(ratios,ages,by.x="ChildID",by.y="Group.1")->ratios
colnames(ratios)[dim(ratios)[2]]<-"Age"

#cbinding results in text, so we numerize the ratios
for(thisvar in c("z_lr","z_cr","l_lr","l_cr")) ratios[,thisvar]=as.numeric(as.character(ratios[,thisvar]))
summary(ratios)

```

```

##      ChildID      z_lr      z_cr      l_lr
## 1111_1 :1  Min.   :0.7625  Min.   :0.02473  Min.   :0.8219
## 1151_1 :1  1st Qu.:0.8976  1st Qu.:0.03569  1st Qu.:0.9387
## 1801_1 :1  Median :0.9303  Median :0.06496  Median :0.9659
## 2881_1 :1  Mean    :0.9120  Mean    :0.09207  Mean    :0.9523
## 3021_1 :1  3rd Qu.:0.9535  3rd Qu.:0.12083  3rd Qu.:0.9833
## 3041_1 :1  Max.    :0.9678  Max.    :0.23267  Max.    :1.0000
## (Other):4
##      l_cr      Age
## Min.   :0.01429  Min.   :11.83
## 1st Qu.:0.06697  1st Qu.:23.11
## Median :0.07990  Median :43.78
## Mean    :0.10326  Mean    :35.49
## 3rd Qu.:0.11944  3rd Qu.:46.27
## Max.    :0.23944  Max.    :53.26
##

```

We first look generally at two measures that have been found to relate to age:

- linguistic ratio = (“Canonical”+“Non-Canonical”)/“All vocalizations” (i.e. we remove junk)
- canonical ratio = “Canonical”/(“Canonical”+“Non-Canonical”) (i.e. we remove junk + non-linguistic vocalizations)

As expected, linguistic ratio goes up with age.

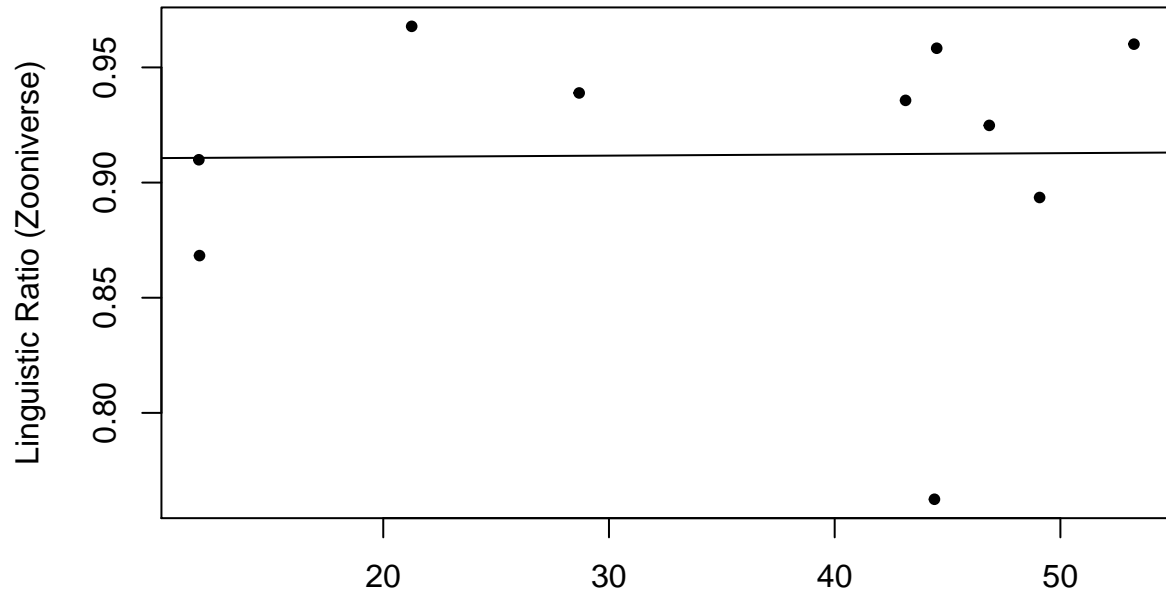
Surprisingly, canonical ratio goes DOWN with age.

```

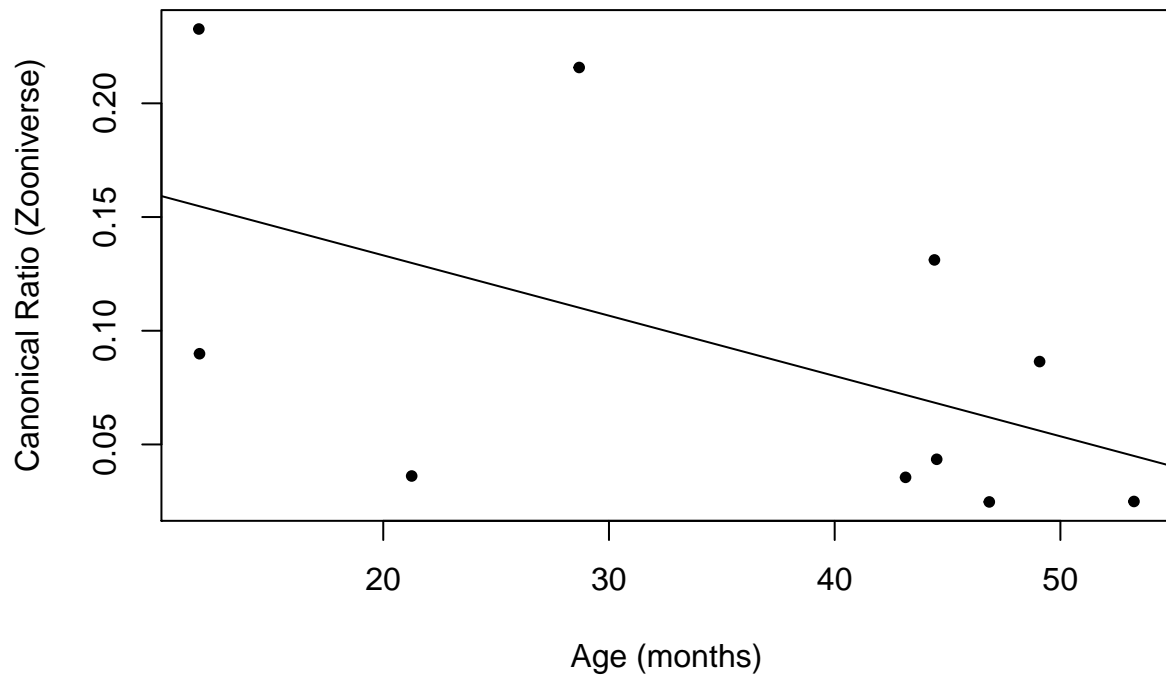
prettynames=c("Linguistic Ratio (Zooniverse)","Canonical Ratio (Zooniverse)",
              "Linguistic Ratio (Lab)","Canonical Ratio (Lab)" )
names(prettynames)<-c("z_lr","z_cr","l_lr","l_cr")
for(thisvar in c("z_lr","z_cr","l_lr","l_cr")) {
  myr=round(cor.test(ratios[,thisvar],ratios$Age)$estimate,3)
  plot(ratios[,thisvar]~ratios$Age, pch=20,xlab="Age (months)",ylab=prettynames[thisvar],main=paste0("r",myr))
  abline(lm(ratios[,thisvar]~ratios$Age))
}

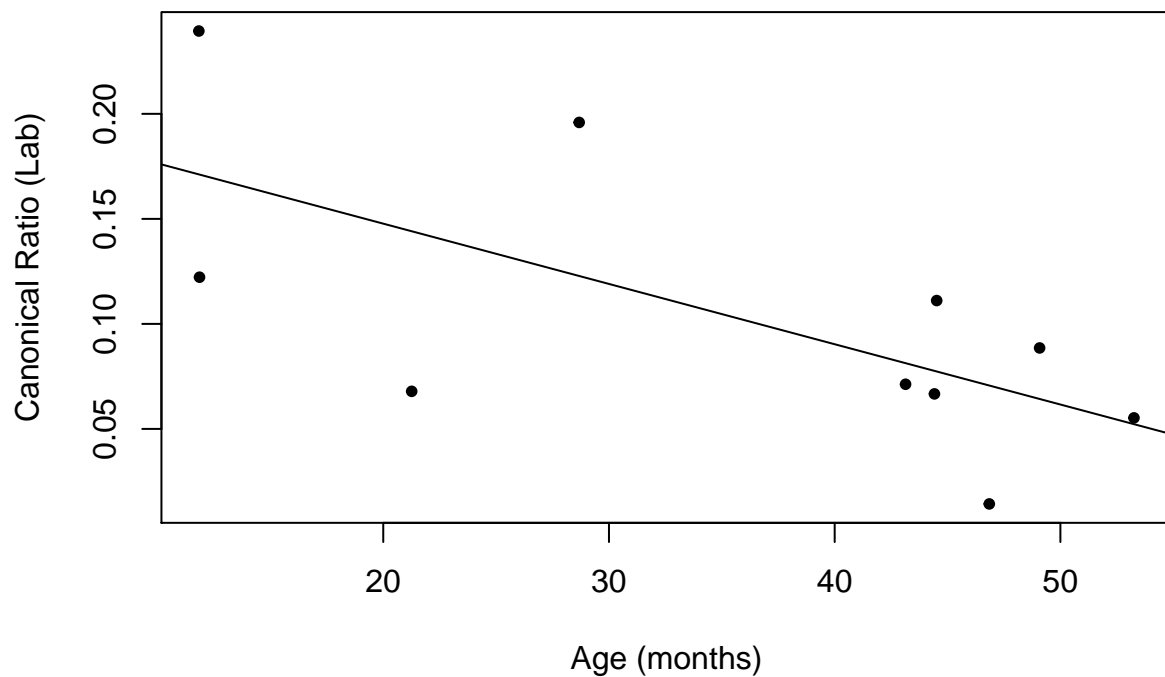
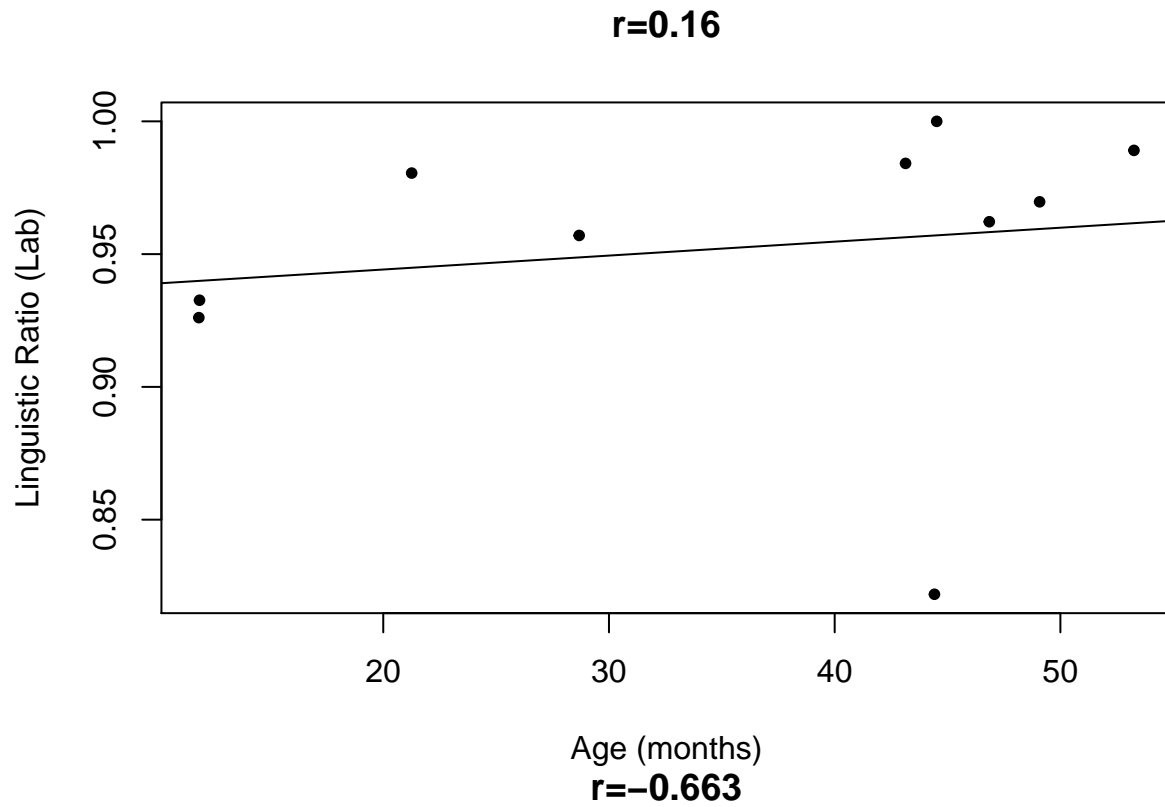
```

$r=0.014$



Age (months)
 $r=-0.536$





But the key thing for us: Are Zooniverse annotations describing children similar to lab annotations? The answer is clearly yes.

```
#Ling ratio
pdf("ling_rat_z_vs_l.pdf",height=5,width=5)
lims=range(c(ratios[, "z_lr"],ratios[, "l_lr"]))
```

```

myr=round(cor.test(ratios[, "z_lr"], ratios[, "l_lr"])$estimate, 3)
plot(ratios[, "z_lr"] ~ ratios[, "l_lr"], pch=20, xlab=prettynames["l_lr"], ylab=prettynames["z_lr"], main=p
      xlim=lims, ylim=lims)
abline(lm(ratios[, "z_lr"] ~ ratios[, "l_lr"]))
lines(c(0, 1), c(0, 1), lty=2, col="darkgray")
dev.off()

```

```

## pdf
## 2

```

```

#CR
pdf("can_rat_z_vs_l.pdf", height=5, width=5)
lims=range(c(ratios[, "z_cr"], ratios[, "l_cr"]))
myr=round(cor.test(ratios[, "z_cr"], ratios[, "l_cr"])$estimate, 3)
plot(ratios[, "z_cr"] ~ ratios[, "l_cr"], pch=20, xlab=prettynames["l_cr"], ylab=prettynames["z_cr"], main=p
      xlim=lims, ylim=lims)
abline(lm(ratios[, "z_cr"] ~ ratios[, "l_cr"]), col="darkgray")
lines(c(0, 1), c(0, 1), lty=2, col="darkgray")
dev.off()

```

```

## pdf
## 2

```