

Using R to assess Eye-tracking data when investigating Psychological Processes

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Data from PhD

“Developmental influences on Anxiety related Attention biases in Four to Eight-year-olds: An Eye-tracking Study”

Why Anxiety?

- One of the most prevalent disorder in children and young people:
 - clinical anxiety affects around 3% of children in the UK aged 5-16 years
 - 6.5% worldwide
- Negative Outcomes
 - negatively impacts school attendance and social competence
 - associated with depression and suicidal ideation in later life
 - Widen than individual:
 - Family processes
 - Economic burden – cost of treatment (indirect and direct)

What is known

- Cognitive models of anxiety implicate cognitive biases as having a predisposing/causal/maintaining role on anxiety.
- Attention bias: attention is disproportionately allocated to threat
 - Meta-analysis found a robust association between attention bias and anxiety across studies
 - Present in adults and children (small sample)

Children: What is known?

Attention bias

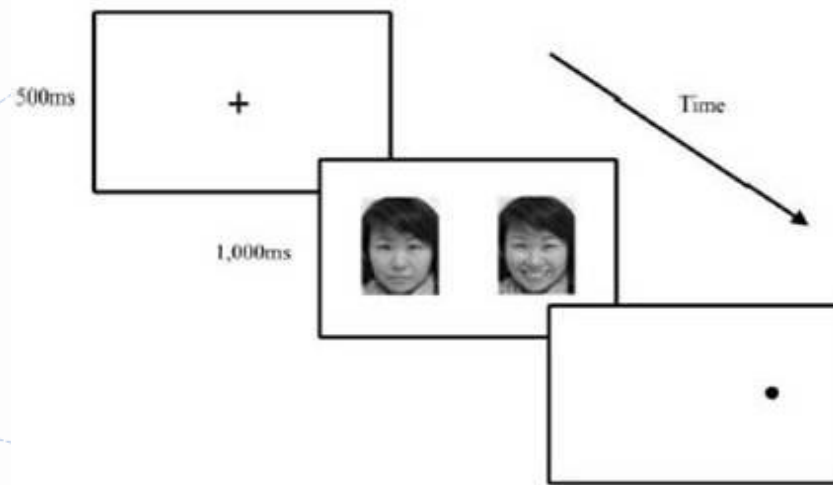
- Meta-analysis (Dudeney, Sharpe, & Hunt, 2015)
 - A robust relationship between attention bias and anxiety in children and adolescents
 - Moderated by
 - Age

Moderation by Age

- Mean age of the studies around 11 years of age
- Age range of studies included : 4 to 18 year olds
 - only a few studies included the younger ages

Why the gap?

- Methodological limitations
 - Most common ways of assessing cognitive biases in adults are not appropriate for young children



Dot probe

Eyetracking

- reliable, unobtrusive, and continuous measure of visual attention
- be employed in a free-view procedure
- Used with children to assess anxiety-related biases
 - Mueller et al., 2012; Shechner et al., 2013; In-Albon, Kossowsky, & Schneider, 2010; Price et al., 2013; Gamble and Rapee., 2010; **Dodd et al., 2015**

Eyetracking Task

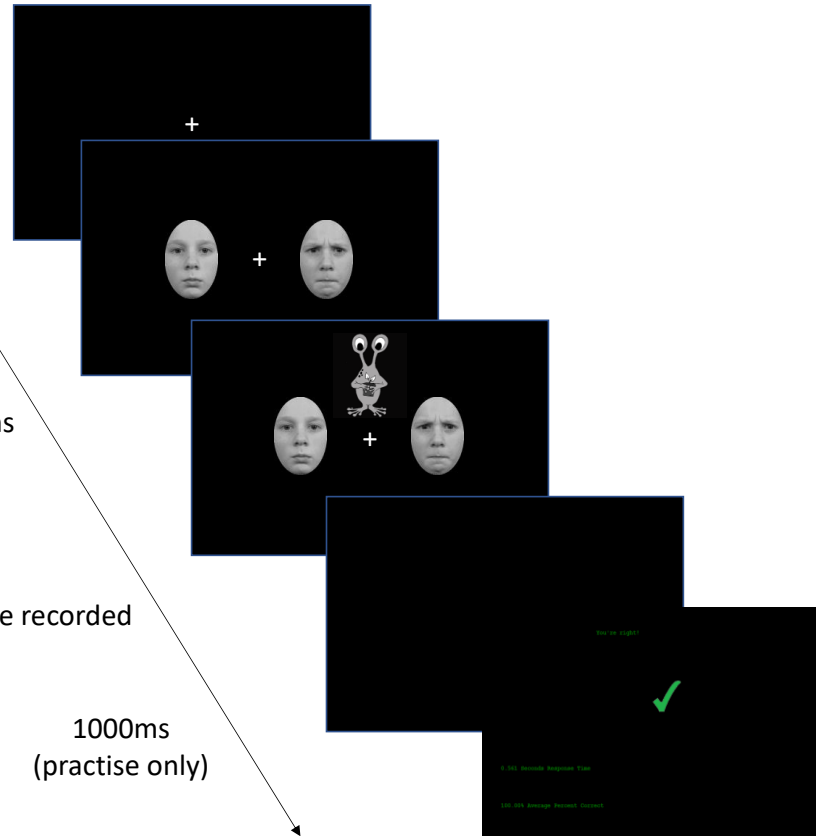
50-100ms
+ gaze contingency
threshold 100ms

1500- 2000ms

1000ms

Until response recorded

1000ms
(practise only)



Participants

- Community sample: recruited through advertising
- 104 children (62 males, *Mage* = 6.02, *SD* = 1.15, age range 4.08 to 8.83 years olds)
- Children were split into high and low anxious groups on the basis of parent report during screening, 65 children were in the high anxious group.

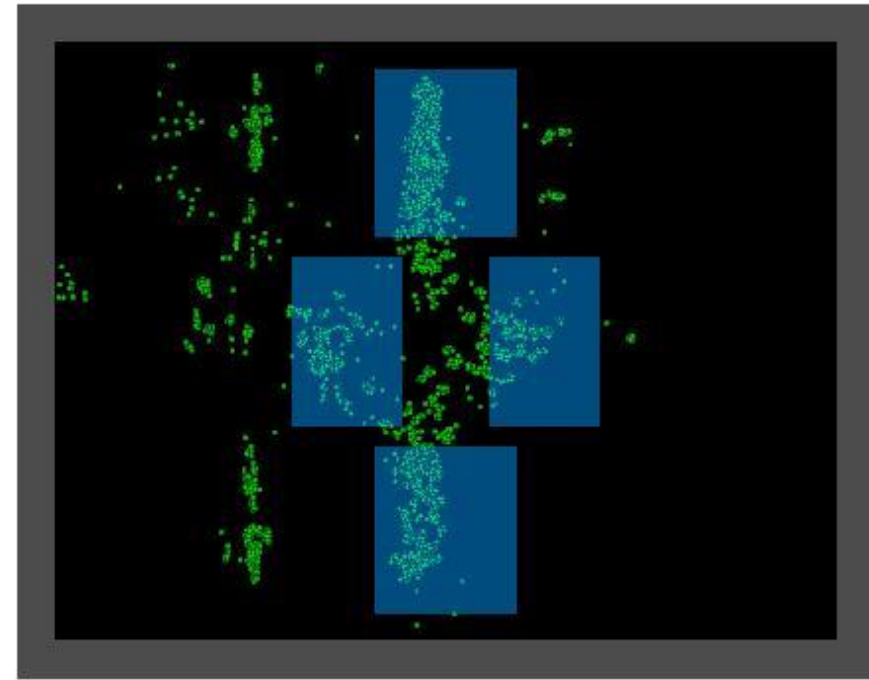
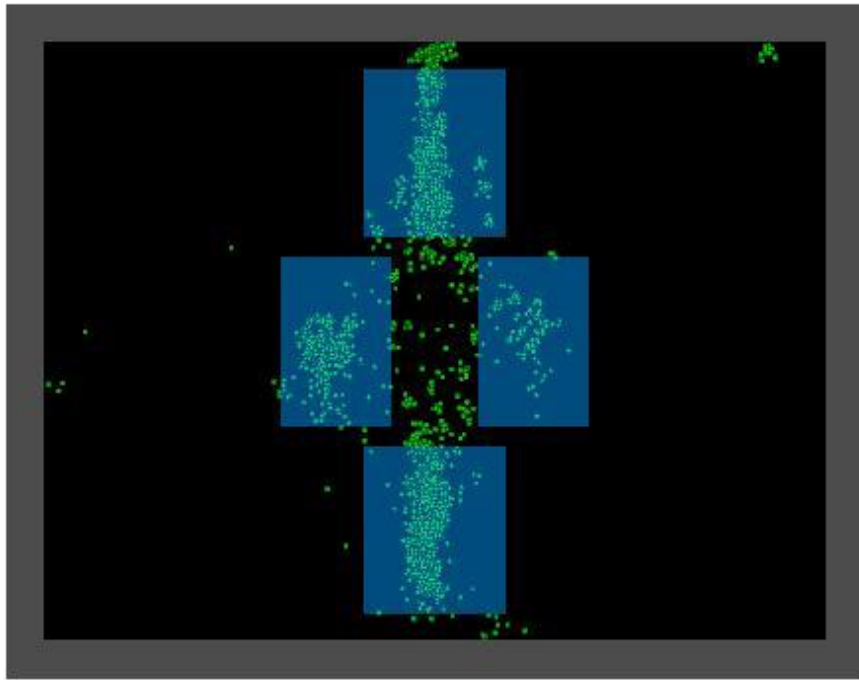
Measures

- Developmental proxies:
 - Age
 - Effortful Control Scale – Children's Behaviour Questionnaire (CBQ: Rothbart, 2001)
 - Cognitive abilities: Block Design subtask of WIPPSI-VI
 - Non-verbal Linguistic Abilities: Language Comprehension subtask of WIPPSI-VI
- Other measures
 - Autistic Quotient (AQ; Auyeung, Baron-Cohen, Wheelwright, & Allison, 2008)

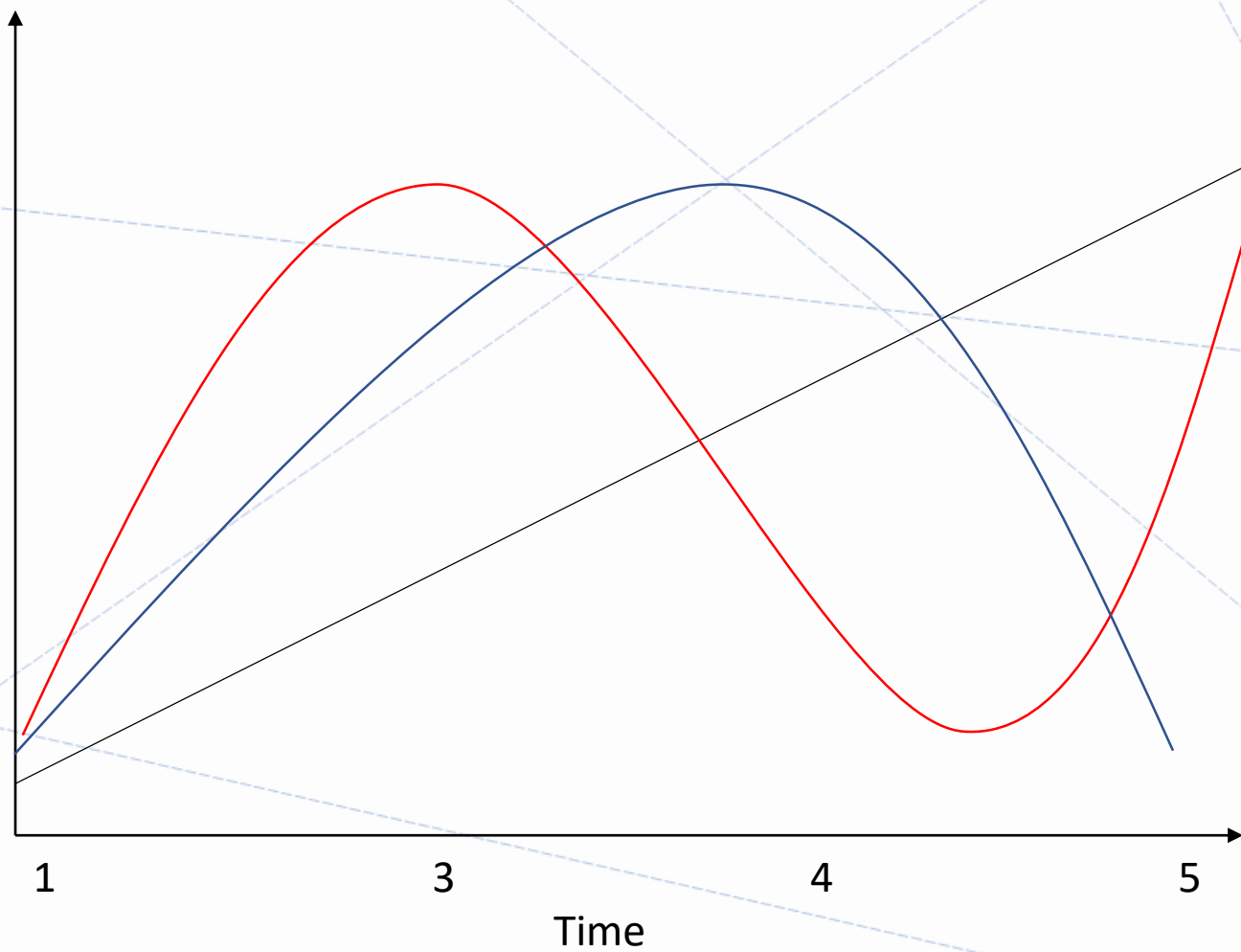
Eyetracking

- Data Cleaning
 1. Visual Check for Calibration issues
 2. Check whether the children were indeed looking in the centre of the screen prior to the onset of the faces
 3. Removal of any trials with 40% or more invalid observations
- Invalid being where the eyetracker was not able to record their eyes, they were looking off screen for example

Eyetracking: Data Cleaning



Growth Curve models

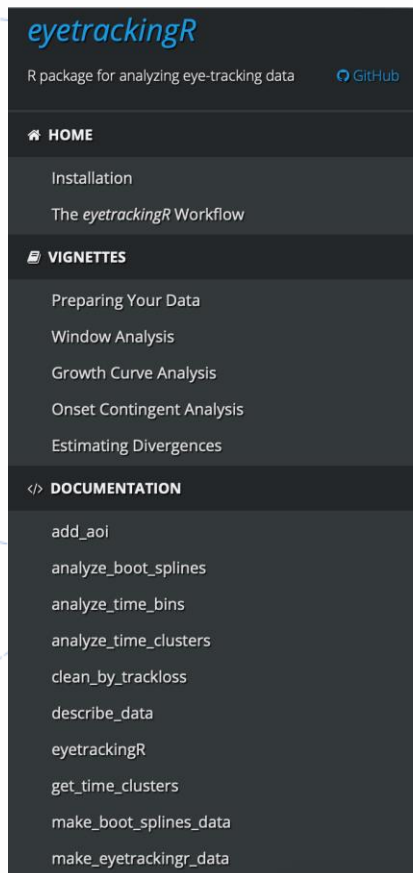


Eyetracking

- Growth Curve Modelling (Mirman et al., 2008)
 - EyetrackingR
 - Just use first looks
 - Time course split into 50ms time bins
 - DV: Proportion of observations per bin where participant is looking at an emotional face
 - DV bias: $\text{Proportion participant at an emotional face} - \text{Proportion participant looking at a neutral face}$

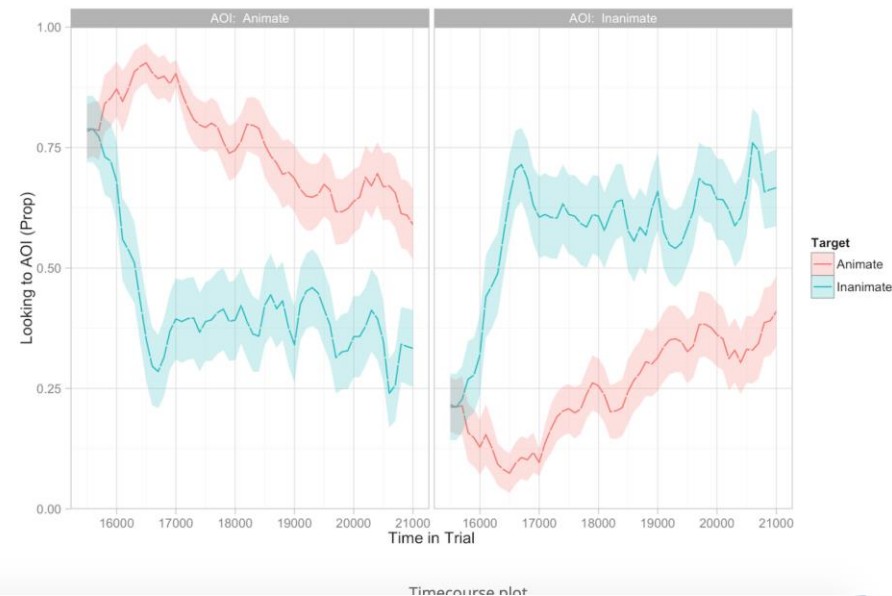
EyetrackingR

- <http://www.eyetracking-r.com>



What is *eyetrackingR*?

eyetrackingR is an R package designed to make dealing with eye-tracking data easier. It handles tasks along the pipeline from raw data to analysis and visualization -- as illustrated in [the eyetrackingR workflow](#). Check out the vignettes to the left for some gentle introductions to using eyetrackingR for several popular types of analyses, including growth-curve analysis, onset-contingent reaction time analyses, as well as several non-parametric bootstrapping approaches.



EyetrackingR: Data Prep

```
ABData<-read.csv("Firstlook.csv", header = T, sep=",")
```

```
#this prepares the eyetracking data for analysis
```

```
data("ABData")
```

```
data <- make_eyetrackingr_data(ABData,  
    participant_column = "Subject",  
    trial_column = "TrialId_Continuous",  
    time_column = "RTTime",  
    trackloss_column = "ValidityLeftEye",  
    aoi_columns = c("NeutralF", "Emotion", "Angry", "Happy", "IAPS", "Neutral"),  
    treat_non_aoi_looks_as_missing = FALSE,  
    item_columns = c('Emotiontype')  
)
```

```
#analyze amount of trackloss by subjects and trials
```

```
(trackloss <- trackloss_analysis(data = data))
```

```
#remove the trials that have move than 40% trackloss in the trial
```

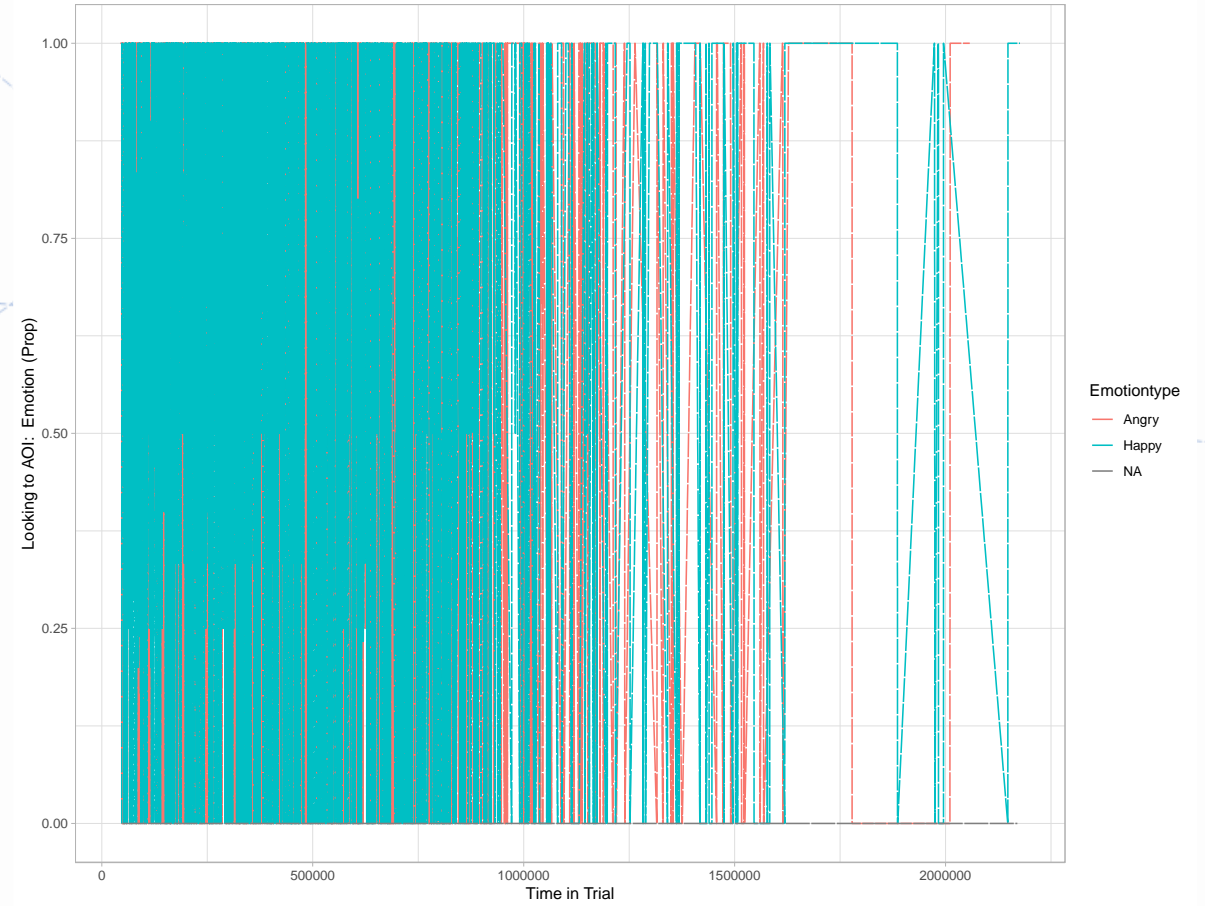
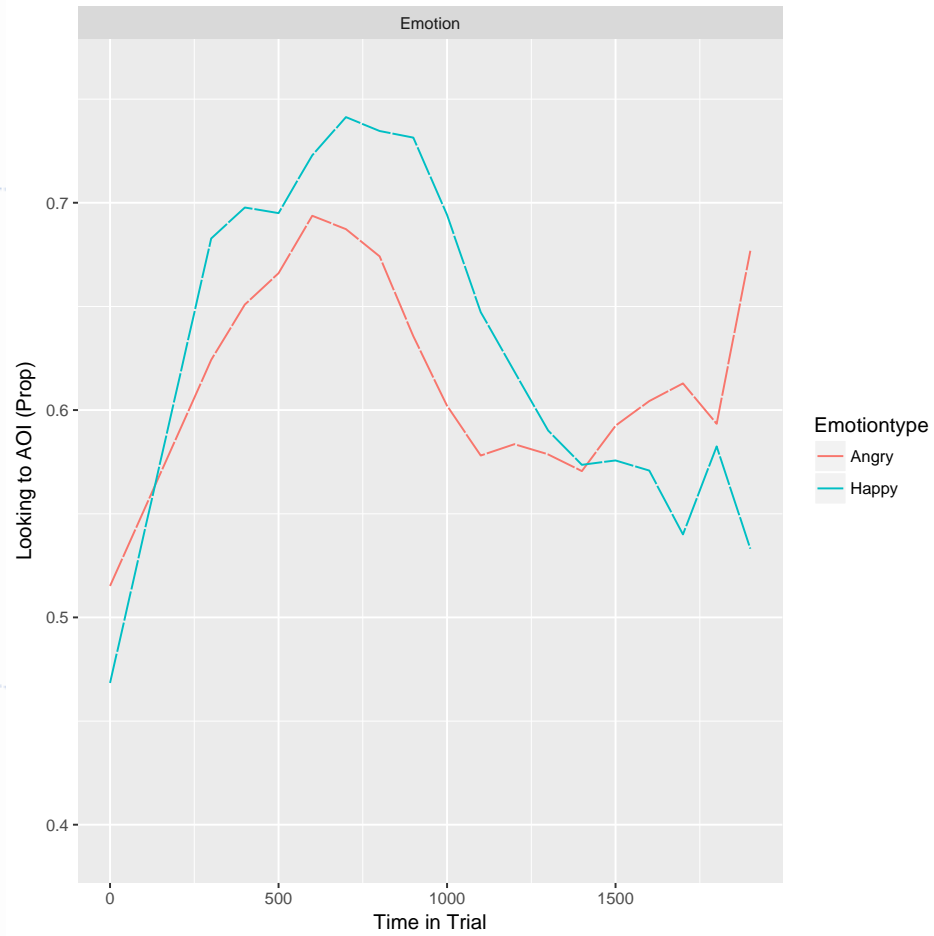
```
data_clean<- clean_by_trackloss(data = data, trial_prop_thresh = .40)
```

```
#set the bin size
```

```
bin_size <- 50
```

```
response_time <- make_time_sequence_data(data_clean, time_bin_size = bin_size,  
    predictor_columns = c("Emotiontype", "HighAn", "ECSTOTAL", "CHyrs", "BlockDesignAgeEquiv", "RecepVocabAgeEquiv", "TOTALAQ"),  
    aois = "Emotion")
```

Issues



Issues

[illegible]

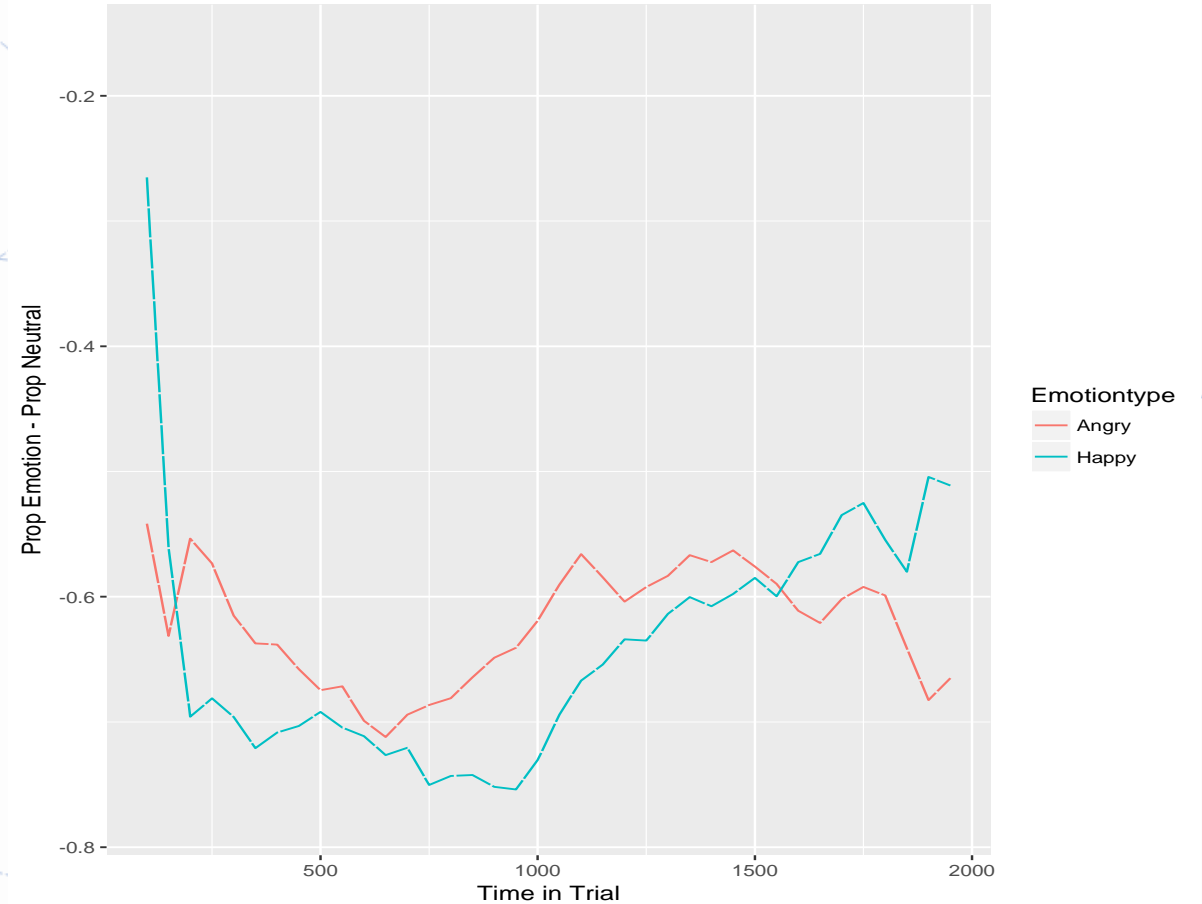
Issues

```
data <- make_eyetrackingr_data(ABData,  
  participant_column = "Subject",  
  trial_column = "TrialId",  
  time_column = "TETTime",  
  trackloss_column = "ValidityLeftEye",  
  aoi_columns =  
  c("NeutralF", "Happy", "Angry", "IAPS", "Neutral", "Emotion"),  
  treat_non_aoi_looks_as_missing = FALSE)
```

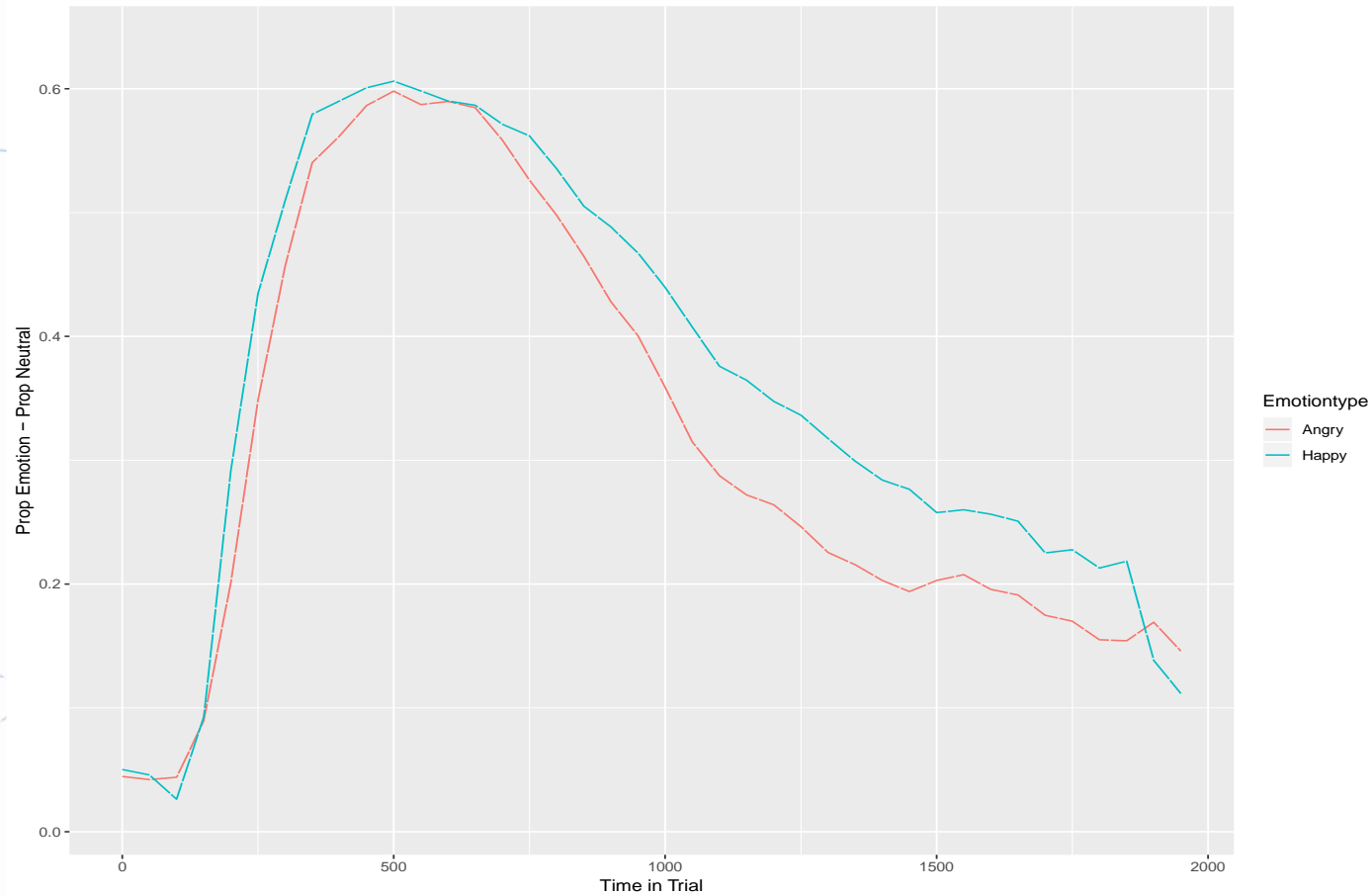
```
data <- make_eyetrackingr_data(ABData,  
  participant_column = "Subject",  
  trial_column = "TrialId_Continuous",  
  time_column = "RTTime",  
  trackloss_column = "ValidityLeftEye",  
  aoi_columns =  
  c("NeutralF", "Emotion", "Angry", "Happy", "IAPS", "Neutral"),  
  treat_non_aoi_looks_as_missing = FALSE,  
  item_columns = c('Emotiontype'))
```

Issue: Bias score

```
# Subtract Prop(Emotion)-Prop(Neutral) for  
each time bin for each subject, within  
emotion type  
df_bias<-  
aggregate(Bias~Subject+Time+Emotiontype+o  
t1+ot2+TOTALAQ+ECSTOTAL+CHyrs+BlockDesi  
gnAgeEquiv+RecepVocabAgeEquiv,  
          with(df_plot,  
data.frame(Subject=Subject, Time=Time,  
Emotiontype=Emotiontype, ot1=ot1, ot2=ot2,  
            TOTALAQ=TOTALAQ,  
ECSTOTAL=ECSTOTAL, CHyrs=CHyrs,  
BlockDesignAgeEquiv= BlockDesignAgeEquiv,  
RecepVocabAgeEquiv=RecepVocabAgeEquiv,  
Bias=ifelse(AOI=='TRUE', 1, -1)*Prop)), sum)
```



Issues: Bias score



EyetrackingR

```
model_time_sequence1s <- lmer(Bias~ EmotionTypeC*(ot1 + ot2) +  
AQ + (1+ot1 + ot2|Subject), data = df_bias, REML=FALSE)  
estimate<-broom::tidy(model_time_sequence1s, effects = "fixed")  
results<-drop1(model_time_sequence1s, ~., test="Chi")
```

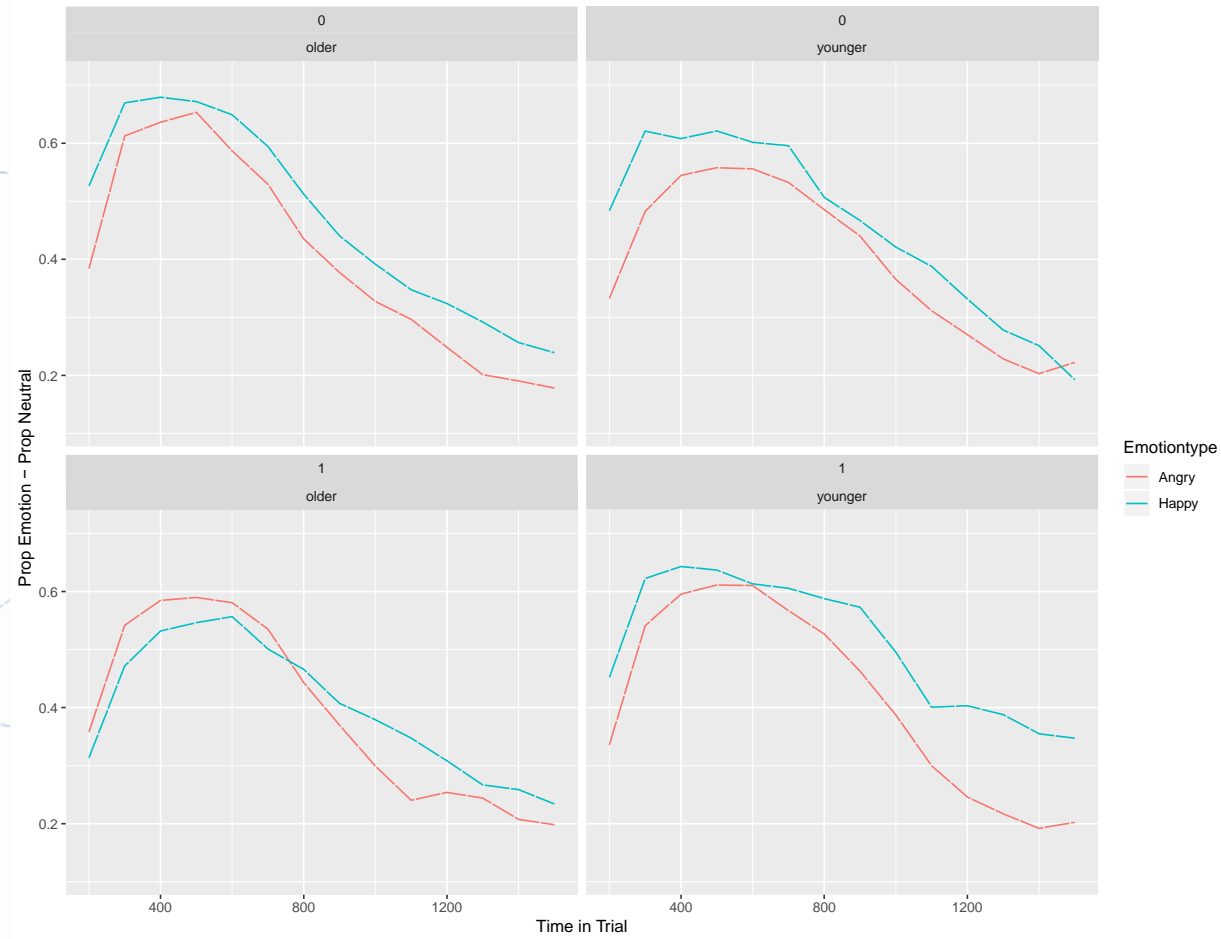
Issue: Choice of polynomials

- Hypotheses:
 - all children will show an initial vigilance to emotional faces
 - this will be stronger for angry faces than happy faces
 - participants with higher levels of anxiety will show increased vigilance for angry faces followed by avoidance,
 - relative to participants with lower levels of anxiety.
 - These anxiety-related effects would be moderated by age
 - anxiety-related avoidance would be stronger in older than younger children

Results

- All children vigilant to emotional faces
 - No support this is particular to angry faces
- Suggestion of avoidance
 - Age influenced this: driven by the younger child

Results



Experiences with R

- Data preprocessing all done in R
- Allowed us to go beyond traditional analysis
- Allowed us to make use of continuous nature of the data using a methodology appropriate for young children
- Visualisation capacity allowed for continuous sanity checks on the data, the analysis and the interpretation