PART 2: GSR Data Analysis

Data Description:

This data is from a study of subjects ranging from 9-23 in age. In the experiment, participants viewed a series of images, separated into blocks. All images in a given block were either positive, negative, or neutral in valence. Further, for some of the blocks, the timing at which these images appeared was highly predictable, because there was a countdown before each image informing the participants when they would see the next picture. These were the predictable blocks. For other blocks, the countdown consisted of meaningless random numbers, so the participants were highly uncertain when an image would appear. These were the unpredictable blocks.

Somerville et al, 2013

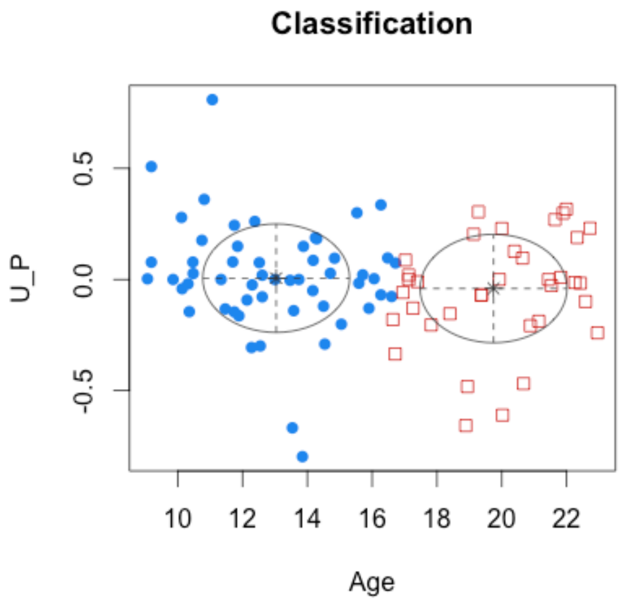
While participants were viewing the images, we used electrodes on their fingertips to passively measure the electrical conductance of their skin, or their galvanic skin response (GSR). This is a widely used measure of physiological arousal; when the sympathetic nervous system is aroused, sweat gland activity increases the conductance of the skin, producing a transient "skin conductance response" (SCR).

Variables:

-*Age*
-*Peaks* – the average **magnitude** of all SCRs in a given block
-*U_P* – the average difference in SCR magnitude between unpredictable and predictable blocks (unpredictable *Peaks* minus predictable *Peaks*)
-*Counts* – the average **number** of SCRs in a given block
-*Intolerance to Uncertainty Scale (IUS)*– A self-report measure of how intolerant a participant is to uncertainty
-*Pred* – whether the images in the block were predictable or unpredictable

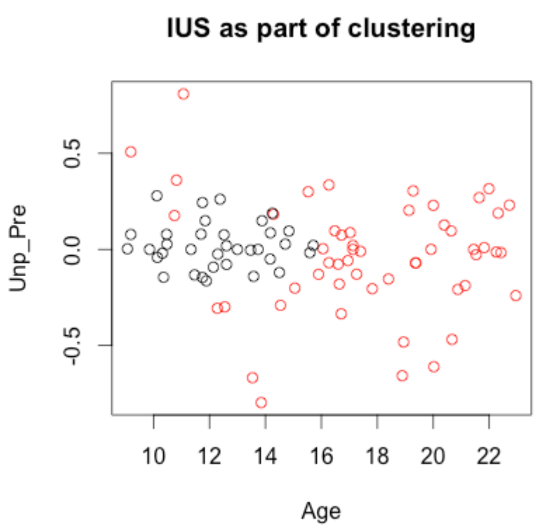
Analyses/Interpretations:

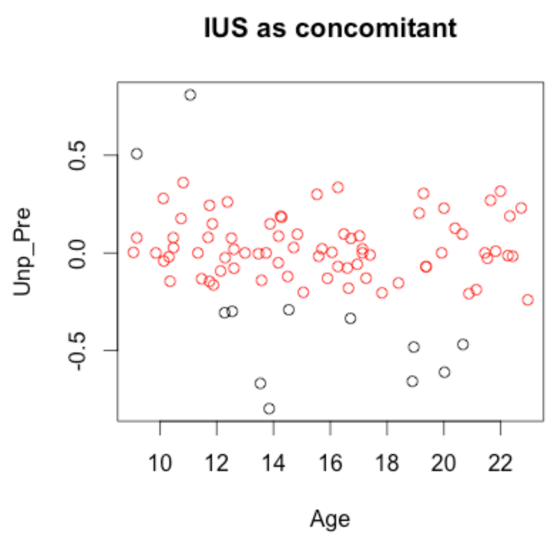
1) In the midterm, we found a relationship between Age and the difference between unpredictable and predictable GSR responses (U_P). We start by clustering by these two variables using the E-M method. This results in a two-cluster solution:



This appears to generate one cluster with primarily adults and another that's primarily kids and adolescents.

When we add IUS to the cluster solution, the results are pretty similar. We also checked how the solution would change if we used IUS as a concomitant variable instead:

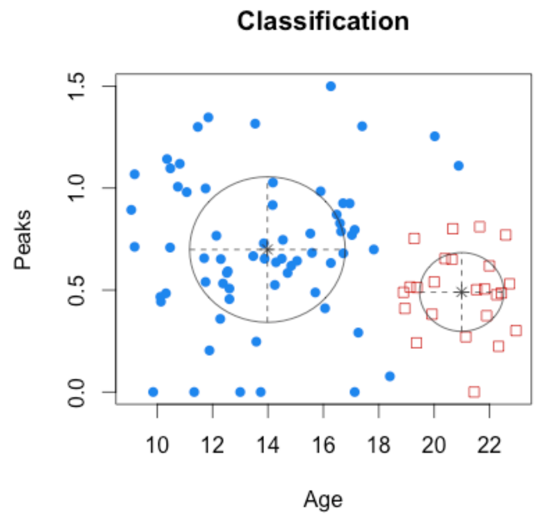


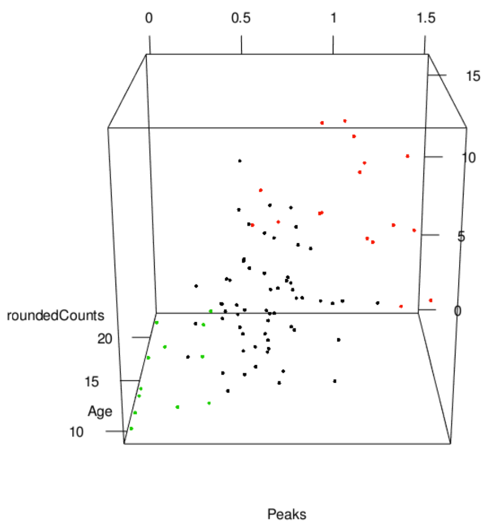


Using the IUS as a concomitant variable seems like a bad cluster solution, basically just making a cluster of the more extreme data points.

2) Using U_P as the dependent variable is not ideal. The better way would be to build a mixture model that uses GSR response as the dependent variable and accounts for predictability as a random effect. We built up this model step-by-step.

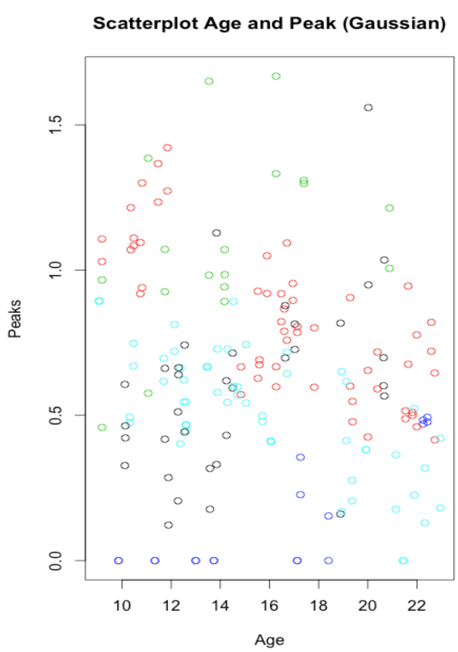
As a starting point, we collapsed across the repeated measure, finding a two-cluster solution when clustering only by Peaks and Age. Once again, one of these clusters consisted primarily of adults, the other primarily of minors.

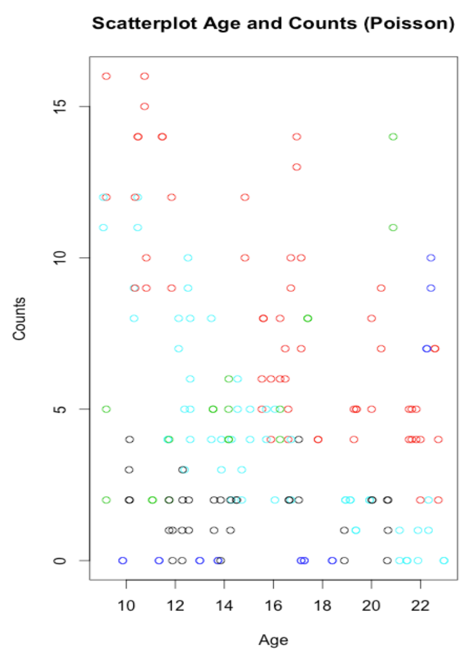




We then added the number of SCRs (Counts), which follows a poisson distribution, into our model. This resulted in a three-cluster solution that is best visualized in 3d.

Next we introduced the repeated measure, with predictability as a random effect nested within subject. As in the previous analyses, we systematically added in Counts and Age to our model. Ultimately, we ended up with a model that included all of the variables of interest, and a five-cluster solution that resulted in a significant effect of age on both peaks and counts in most of the clusters.





These clusters did not look particularly meaningful to us.