PART 1: SES-School Data Analysis

Data Description:

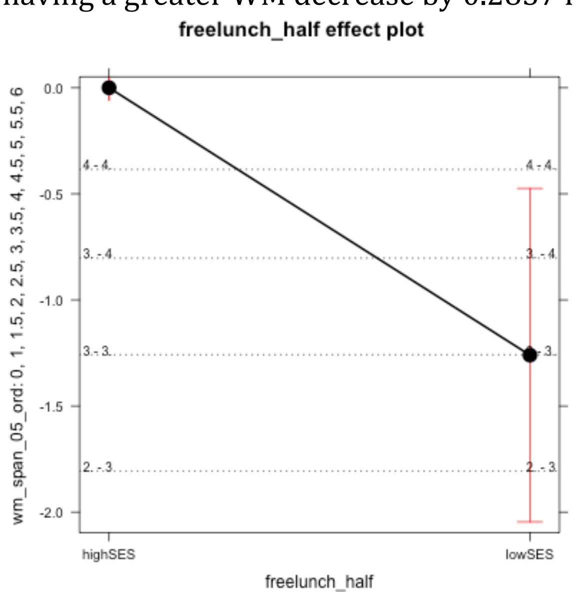
Julia Leonard collected this data set in 2012 while she was a research assistant in Dr. John Gabrieli's lab at MIT. It includes data from 88 8th grade students who were recruited with the intention of looking at how socioeconomic status (SES) affects brain development and behavior. The subjects were split into two SES groups depending on whether they received free/reduced lunch from the government. If they received free/reduced lunch, they were categorized as low SES and if they did not, they were categorized as high SES. To give an example of what this breakdown means, students were eligible for free/ reduced lunch if their family income was below 185% of the poverty line, which approximately translates into less than $42,000 per year per family of two adults and two children. Participants also came from three different types of schools: charter schools, high performing public schools, and low performing public schools.

Variables:

-Age
-*ses_factor / freelunch_half* – SES group
-*wm_span_05* – a measure of working memory, a cognitive trait
-*opportunity_of_nurturance* - the sense that others rely upon one for their well-being (higher = more people rely on you for their well-being)
-*school_group_new* – school type (charter, high performing public, low performing public)
-*GRIT_Average* – a measure of Grit, a non-cognitive personality trait reflecting perseverance and passion for long-term goals
-*MCAS_avg_8* – a composite score of their math and English MCAS (standardized Massachusetts test score) in 8th grade.

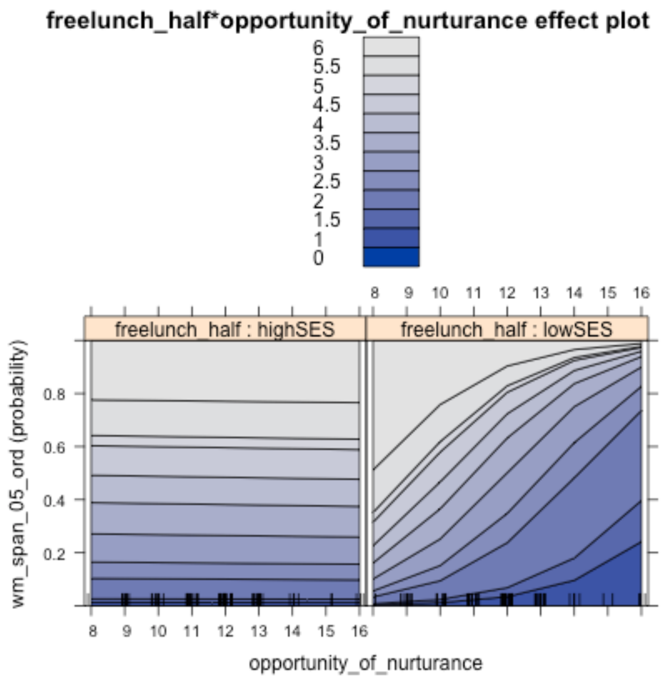
Analyses/Interpretations:

1) We wanted to know if working memory (WM) was related to SES. Since WM is an ordinal variable, we fit a **proportional odds model**. We found that the odds of having a greater WM decrease by 0.2837 for low vs. high SES.

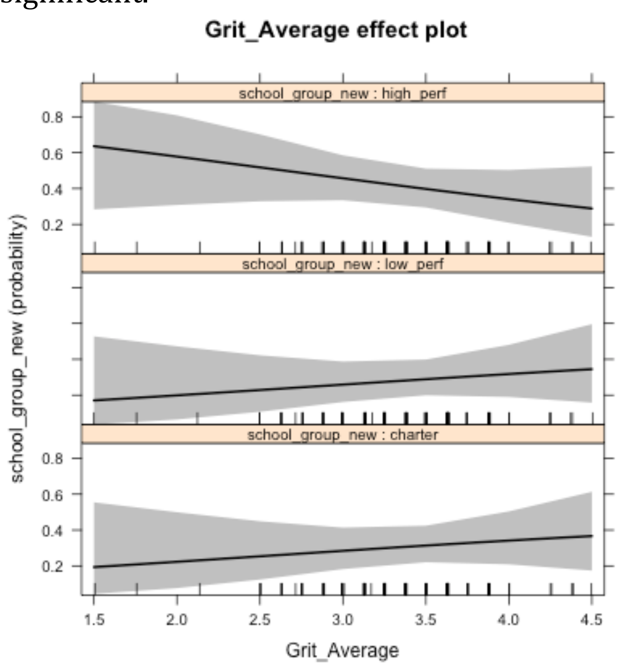


We also noticed a larger variability in WM for low SES, which could be a meaningful effect of low SES or could reflect a sampling bias in terms of heterogeneity in the sampling pools of the two groups.

Work on this data last semester gave us reason to believe that Opportunity of Nurturance might influence this relationship, so we included it as a regressor and found that this second model seemed to do a better job of fitting the data.



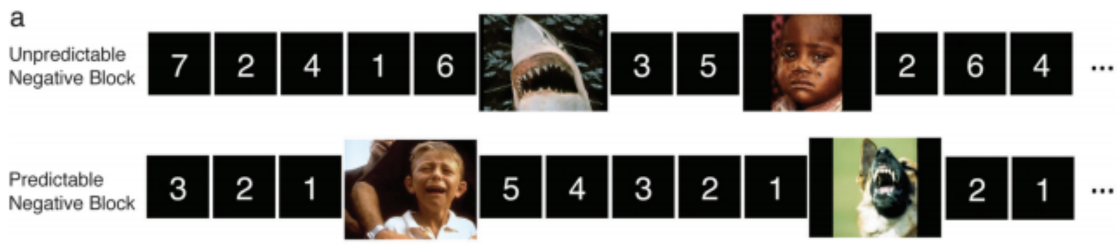
2) We were interested in the relationship between school type and Grit. Since school type is nominal, we fit a **multinomial regression**. The results were completely non-significant.



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:

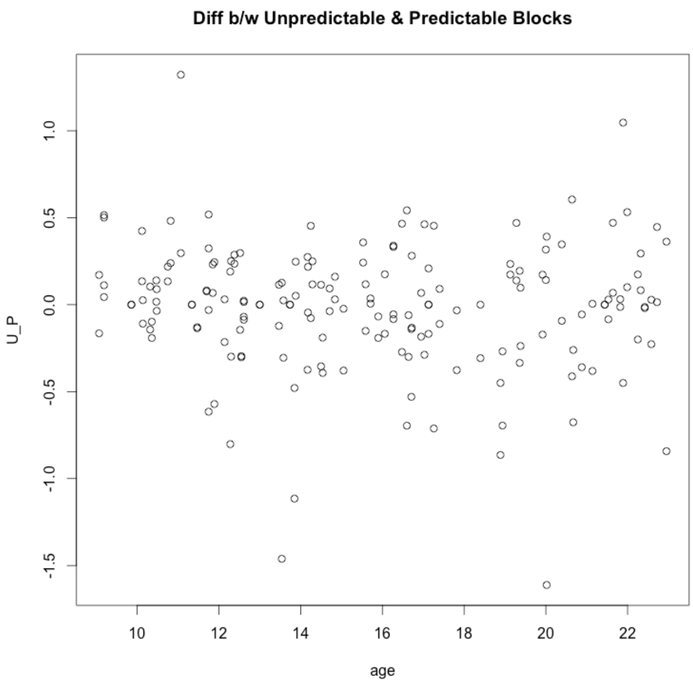
-*age*
-*peaks_fin* – the average magnitude of all SCRs in a given block
-*pred_factor* – whether the images in the block were predictable or unpredictable
-*valence_factor* – the valence of the images in the block. We had no hypotheses about GSR activity during positively valenced pictures, so we removed all positive-valence blocks from the present analysis.

Analyses/Interpretations:

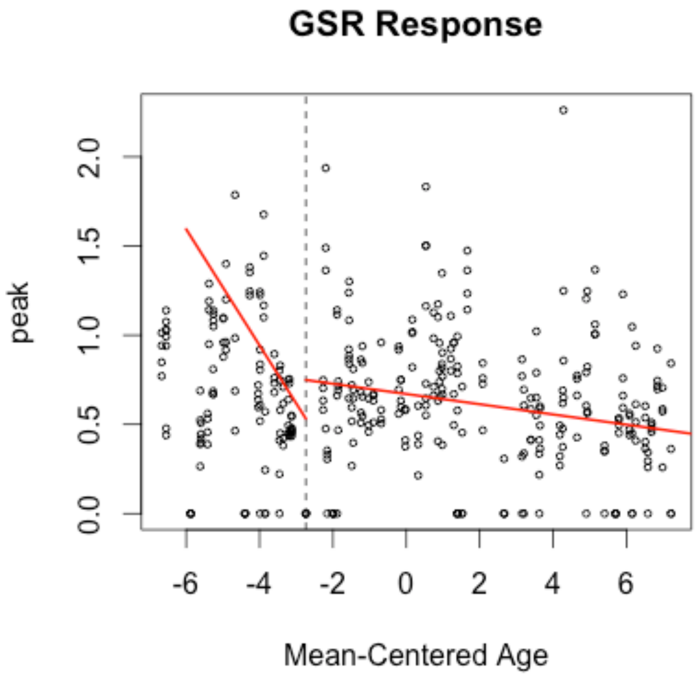
1) We first used this data set to demonstrate a **robust regression**. While this data is in reality a repeated measures design, for this initial demonstration we treated it as if it was not.

2) Our primary question of interest was how the valence and predictability of a block of images influenced a subject's GSR response. Further, our lab studies adolescence and had reason to believe that the response of this age group may be different from children or adults. We assessed this using a **polynomial regression model**, where we looked at the effects of valence and predictability with age as a linear and/or quadratic polynomial. In the quadratic regression, we found a

significant interaction between predictability and quadratic age. To visualize this, the graph below shows the difference in response for unpredictable vs. predictable blocks, and age. We see a slight but significant quadratic trend, which I can't figure out how to add as a curve onto the graph.



3) In a third model, we looked at age as an "adolescent emergent" regressor, creating an age function that curved through childhood but then plateaued. This model slightly outperformed the other two, and still showed the interaction between predictability and the "adolescent-emergent" age regressor. To explore this idea of different relationships before and after adolescence, it would be interesting to do a **segmented regression** with a spline at age 13. We could not get this to work with the current complicated mixed effects model, but we demonstrated the concept using two single linear regressions:


GSR Response
peak
0.0
0.5
1.0
1.5
2.0
-6
-4
-2
0
2
4
6
Mean-Centered Age