Examining Best Model Weights

Joseph Blubaugh

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Overview

The objective of this project is to develop a model capable of detecting texting events from facial expressions. From the previous update the best model is Model 08 which used data segmented into 1/2 second intervals and computed the mean value for each facial expression over the entire interval (15 observations). The goal of this analysis is to extract and analyze the calculated weights in the current best model.

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Neural Network Confusion Matrix (Best Model)

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      Predicted
Actual     0     1
     0 23398  2520
     1  4172 14413

(Training Set) Overall Performance: 0.8391441

      Predicted
Actual     0     1
     0 22738  2941
     1  4735 14089

(Testing Set) Neural Net Overall Performance 0.816965
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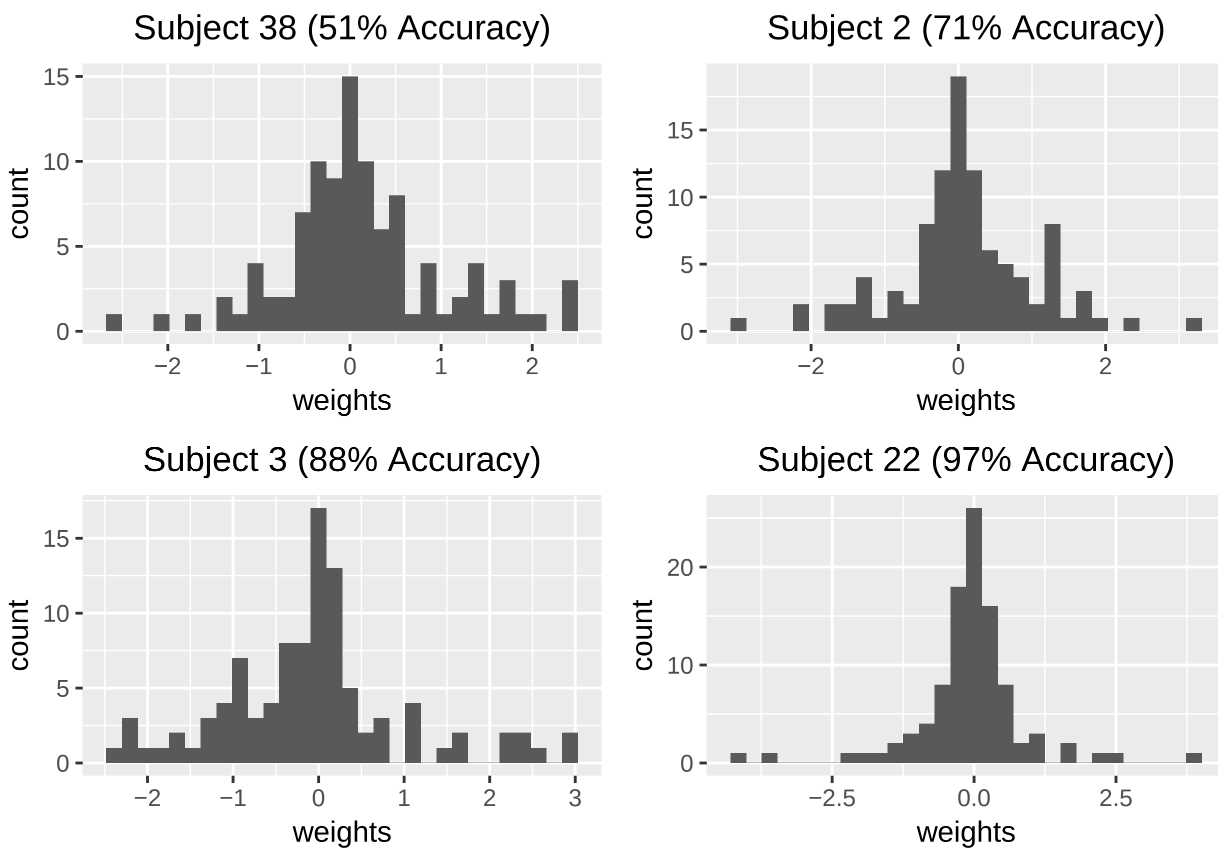
Model Weights

In neural net models, weights are the interconnection between Input_Node -> Hidden_Layer, and Hidden_Layer -> Output_Node. They are analogous to coefficients in regression models. The sum product of the weights and input nodes generates the model output after going through a transformation (activation function). In the case of my current logistic regression setup, the activation function is the sigmoid function (shown in a previous report). In the current best model there are (68 Input Nodes * 100 Hidden Nodes) + (1 Bias Correction * 100 Hidden Nodes) + (100 Hidden Nodes * 1 Output Node) + (1 Output Bias Correction) = 7001 Weights.

Input Nodes	Hidden Nodes	Output Nodes
58 Subjects (1 Base)	100	1
2 Demographics	1 Bias Correction	1 Bias Correction
8 Emotions		

Neural nets do not produce standard errors, tvalues, or pvalues like traditional regression models do for coefficients. In fact neural networks are not really intended to be looked at under the hood. Most of the diagnostics for neural nets rely on examining the differences between training and testing set performance differences. That being said the hidden nodes within a neural net can be thought of as individual logistic regression models. You can extract the weights between the input nodes and the hidden layers and examine the distribution of weights for common indicator variables like age, gender, and subject.

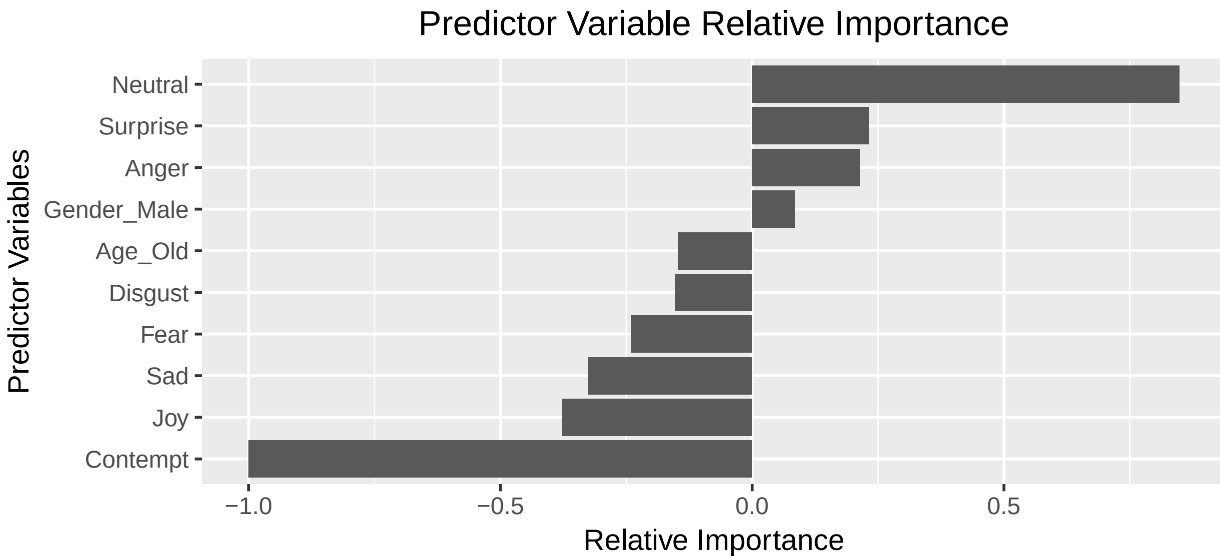


	Subject 38	Subject 2	Subject 3	Subject 22
Min	-3.135314	-3.00098	-2.35483	-4.069946
1st Q	-0.337495	-0.33404	-0.66465	-0.354756
Median	0.009406	0.03642	-0.04398	-0.007874
Mean	0.005288	0.08909	-0.06727	-0.062273
3rd Q	0.331374	0.60957	0.24815	0.257508
Max	3.464602	3.19086	2.97495	3.961502

Looking at a sample of subject weights which includes the worst (subject 38) and the best (subject 22) subjects in terms of model accuracy, there appears to be no real distinction between the weights of the subjects. It turns out that this is a trait of neural networks. Although the hidden nodes can be considered individual models, they are in fact linked in that weights are adjusted based on their combined predictive error. This makes it difficult to infere anything about the weights when you have multiple nodes in a hidden layer.

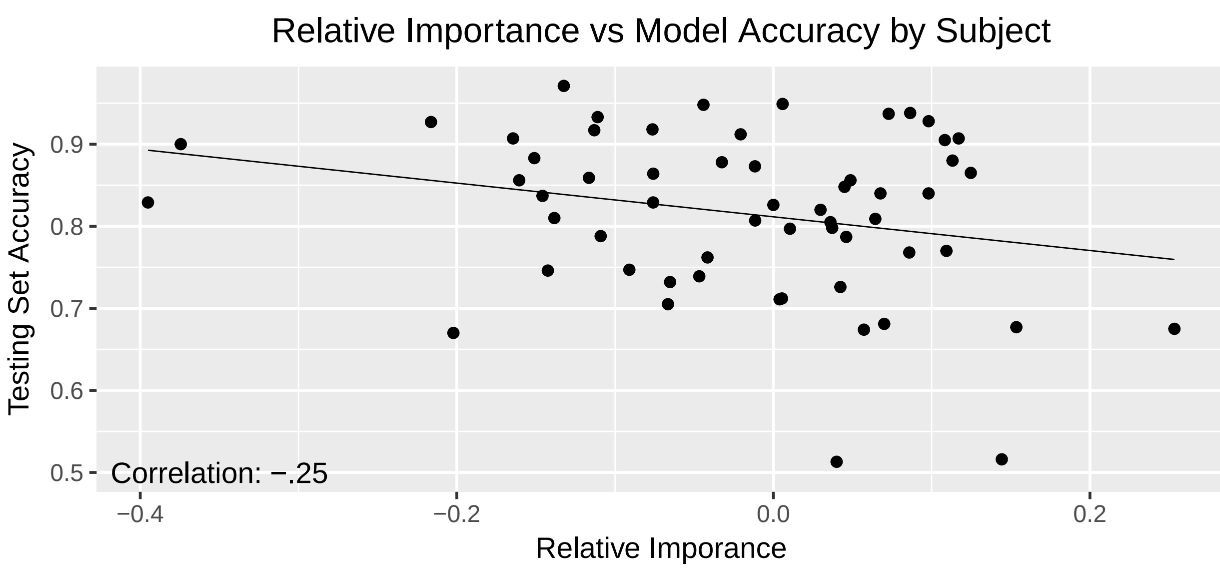
Variable Importance

One way of assessing variable importance is to look at the sum of weights between the input nodes and the hidden nodes. The following plot shows the relative importance of for the 10 predictor variables (Subject not shown) scaled between -1 and 1.



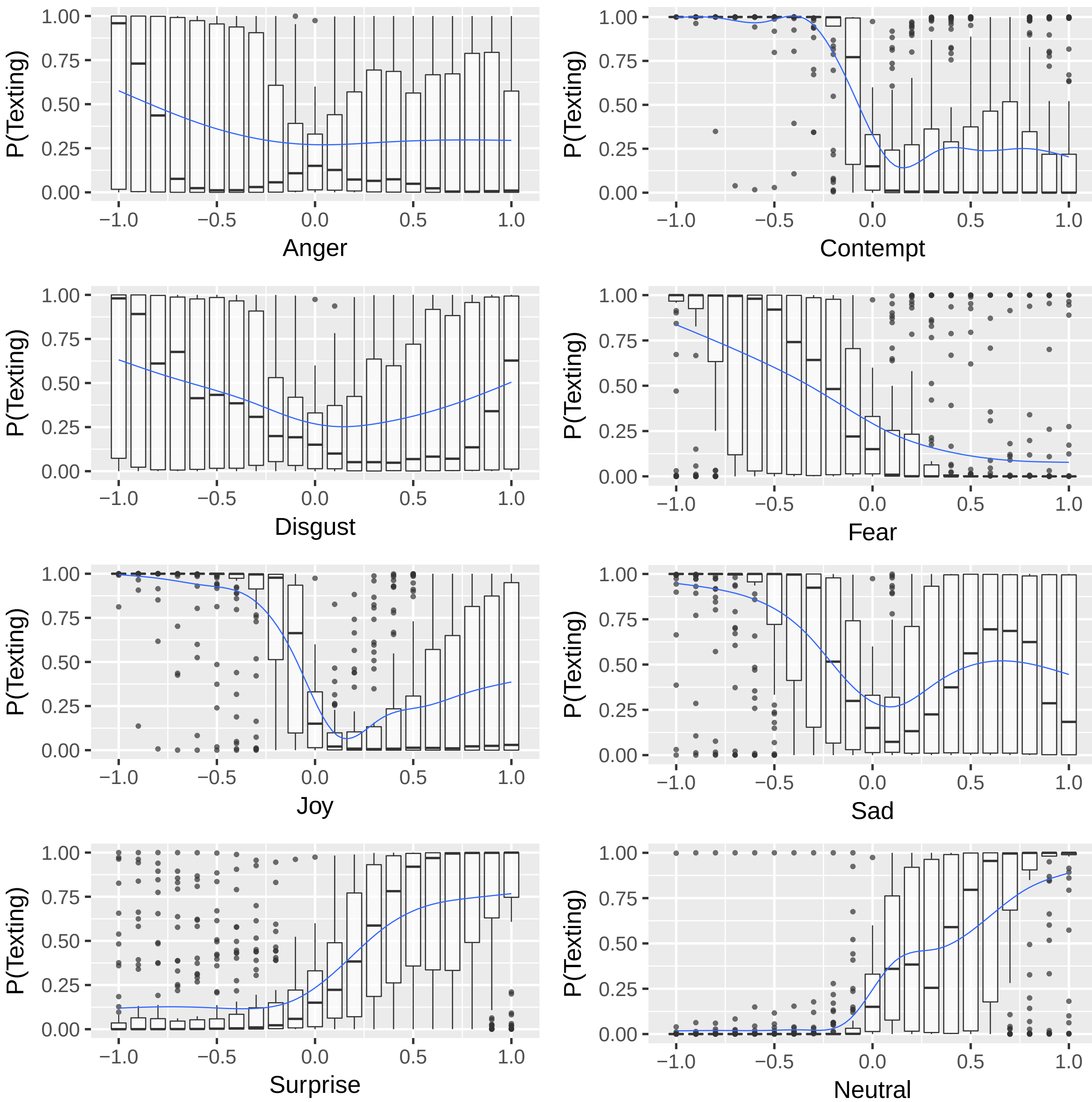
The Neutral emotion has the highest importance, followed by Surprise, Anger, and Gender. Contempt has the lowest importance of all predictors including Subject. The Surprise emotion is a bit surprising that it is the second most important variable because we have seen very little variation in this emotion in previous plots compared to the other emotions. This should be investigated further.

It is also worth looking at the relative importance of the Subject variable since model performance increased significantly when it was added. The importance of Subject is broken out into each factor level. Relative Importance ranges from -.39 to .25. I was interested in seeing how realtive importance and model accuracy are related. There apprears to be some weak correlation between the two.



Emotions Effect on Texting Probability

The following boxplots show the probability of a texting event for each Subject as emotions change. Emotions are represented in intervals of .1 with 0 representing the baseline value of the simulation for that particular Subject. Only the variable on each x-axis is allowed to change, the rest are held constant at the baseline. The current best model was used to predict the probability of a texting event given the range of inputs. There are 59 values for each boxplot, representing the 59 subjects in the simulation.

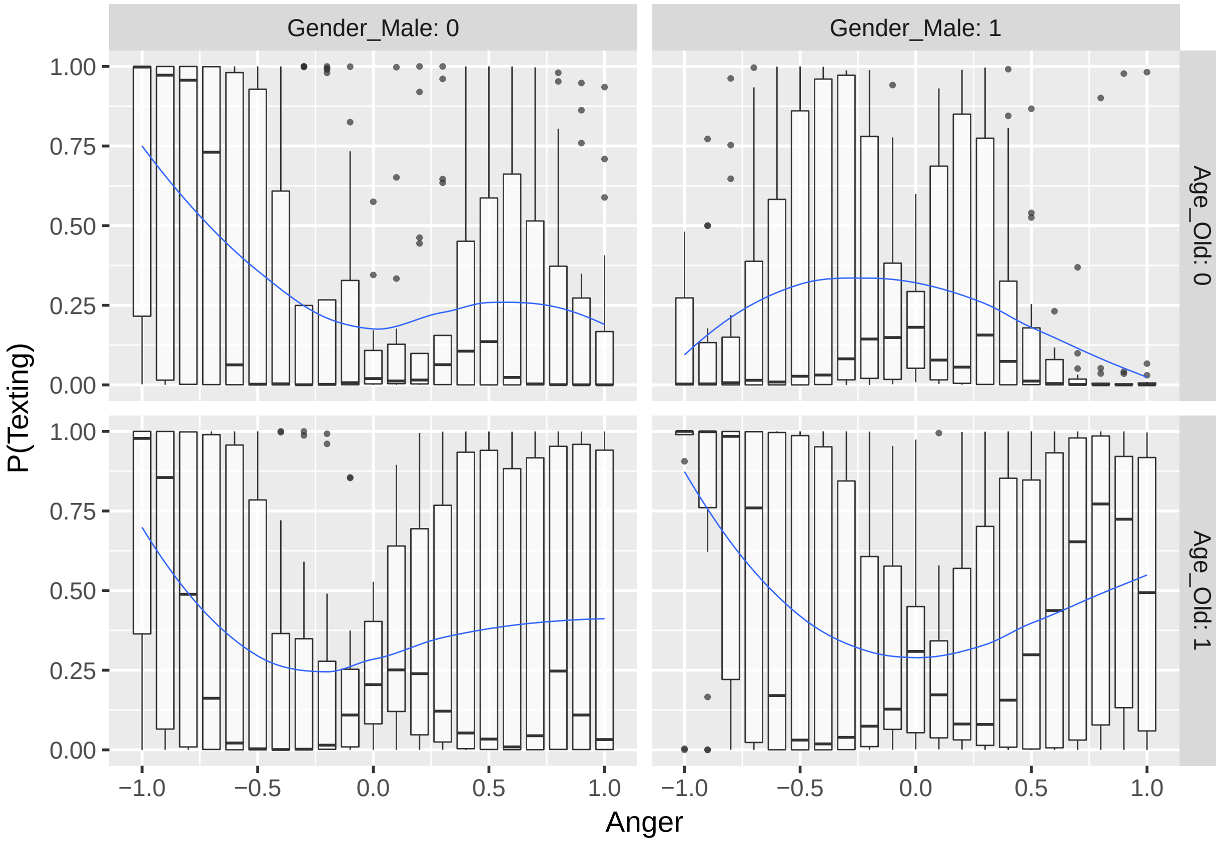


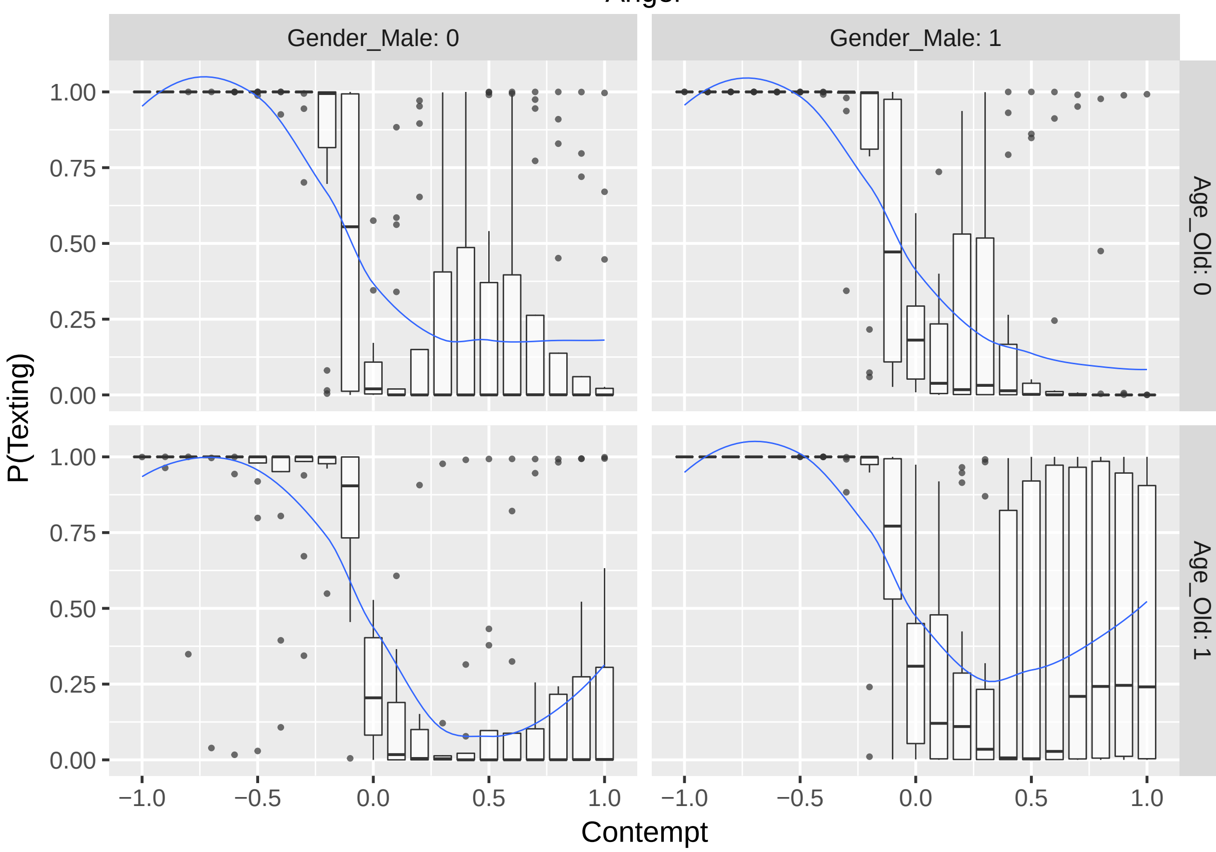
Conclusions and Next Steps

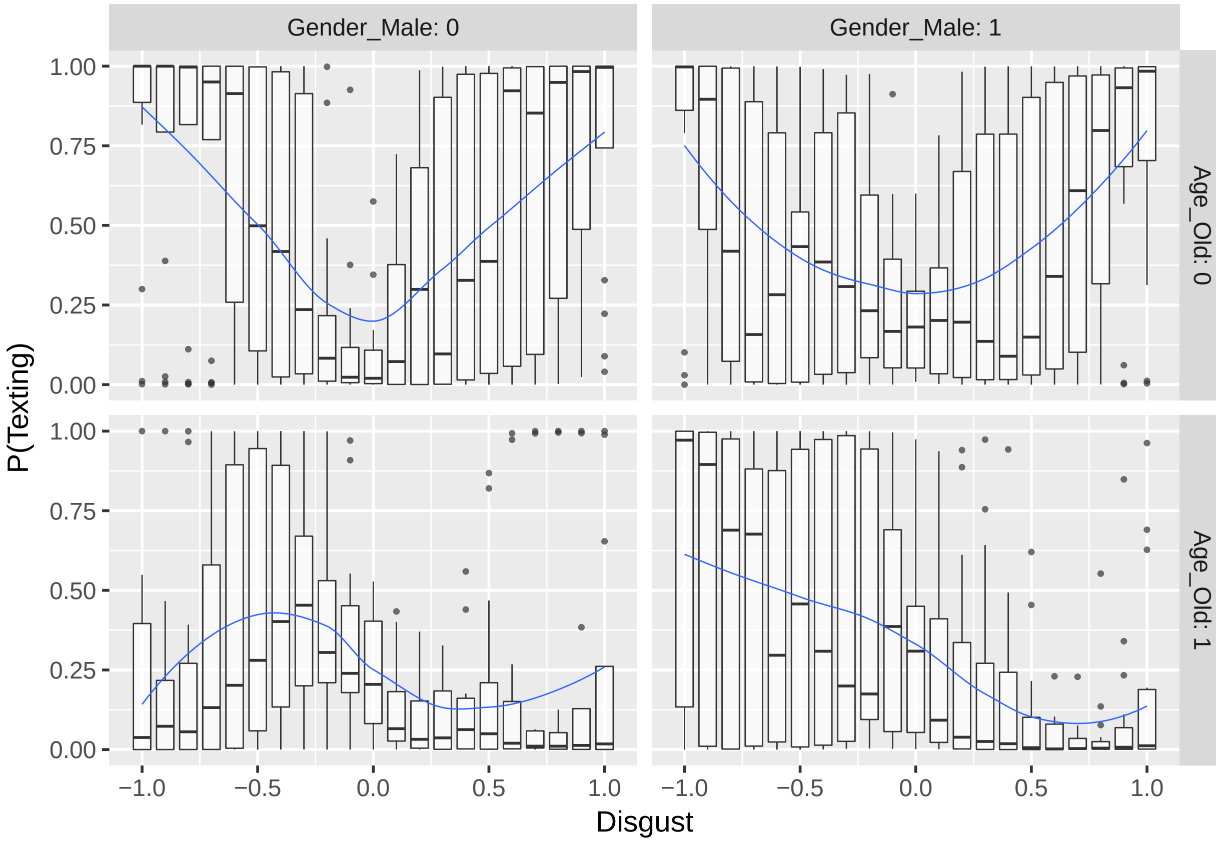
It is not entirely surprising that the Nuetral emotion appears to be the most important variable. Neutral seems to capture the most variation across subjects. I expected the emotions Surprise, Joy, and Fear to have very little importance due to the fact that they are pretty much always at the baseline value. I think some additional investigation into the Surprise emotion is worth looking at to see if its importance can be explained. When looking at the probability model by emotion, broken out by Gender and Age, there appears to be some differences between the groups. My next task will be to look at this interaction and try to come up with some measurable differences between the groups.

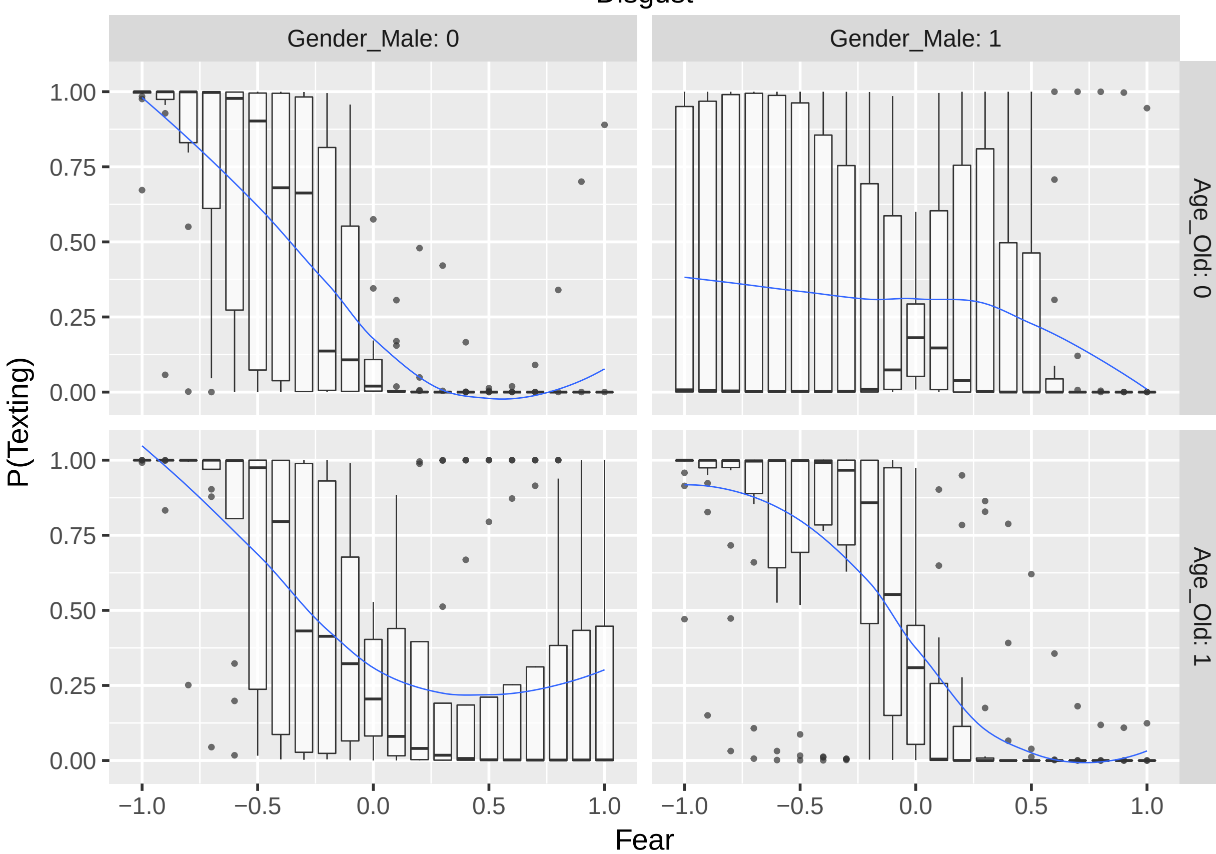
The current model setup uses Subject T001 as the baseline that all other Subjects are compared to. This is a little difficult to explain in the output so I may also try to rearrange the model matrix so that there is no baseline Subject.

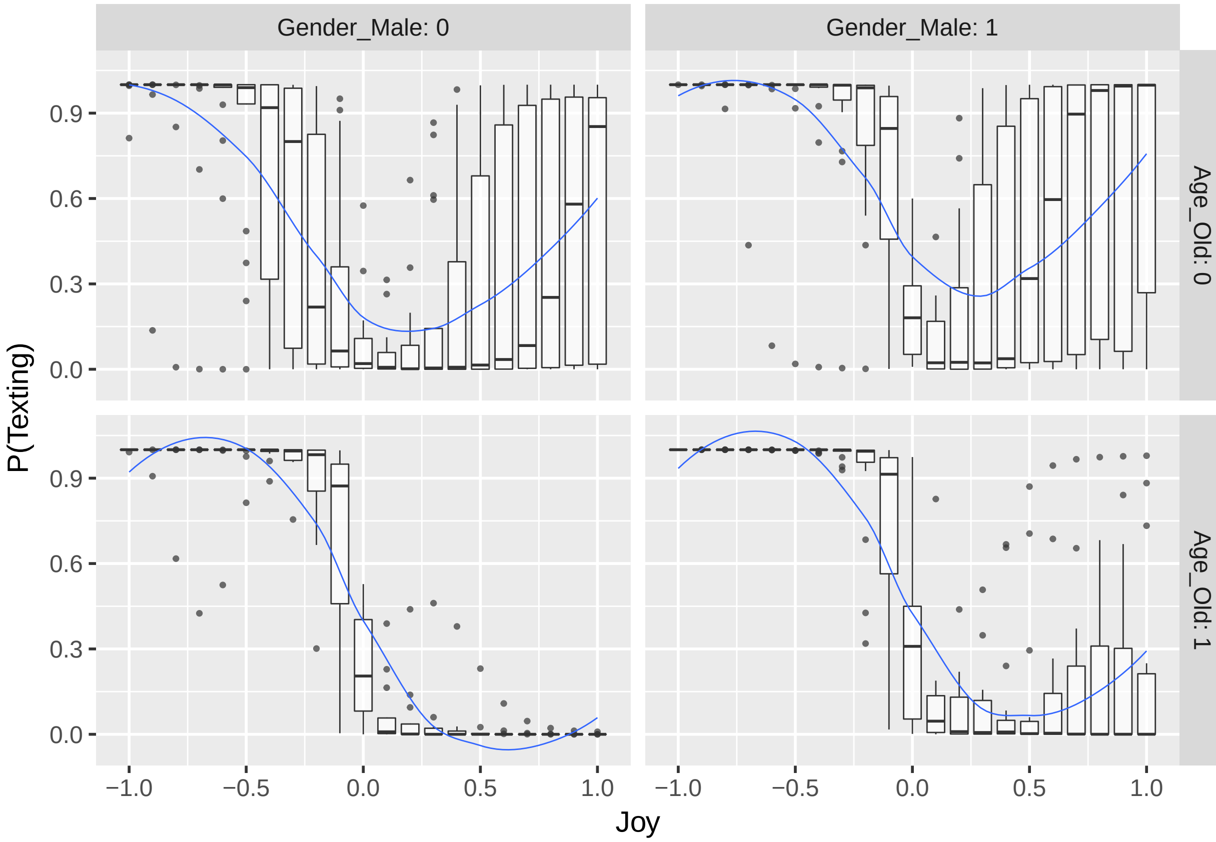
Additional Plots

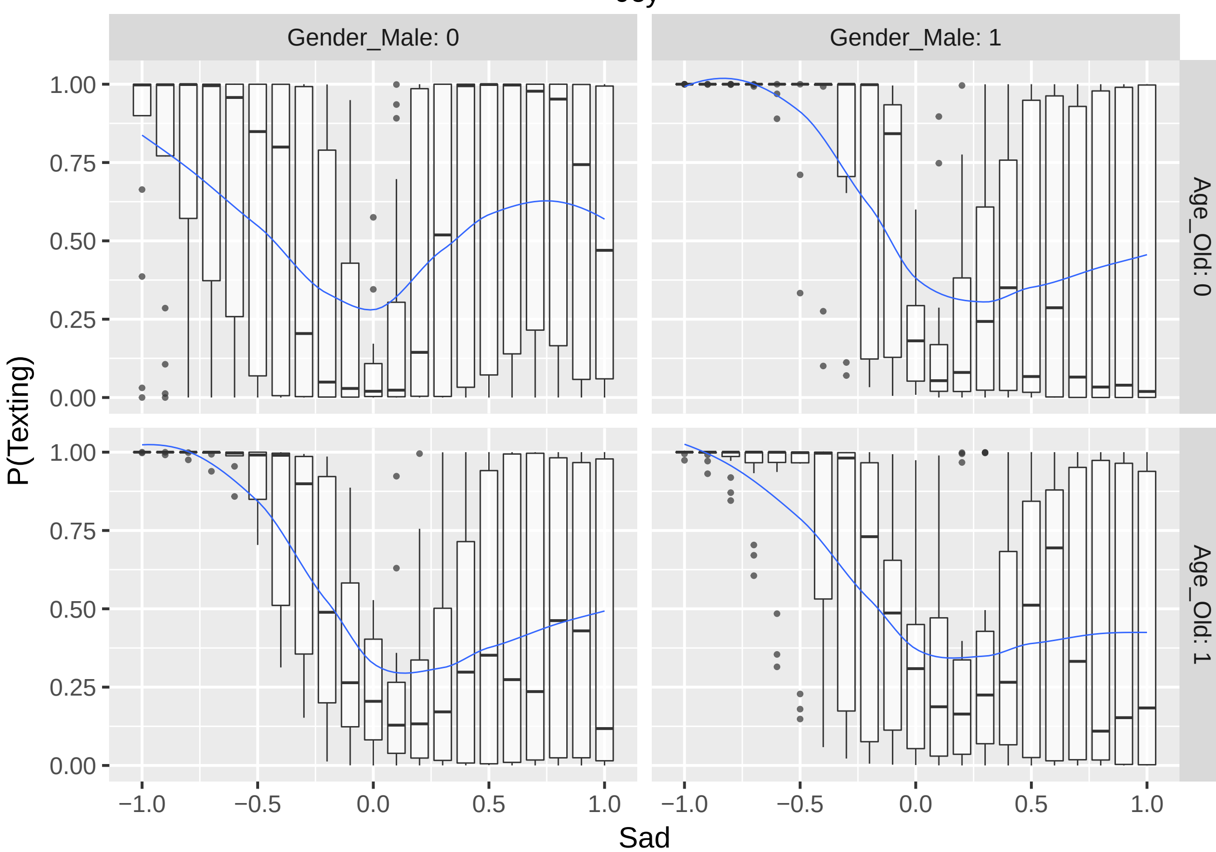


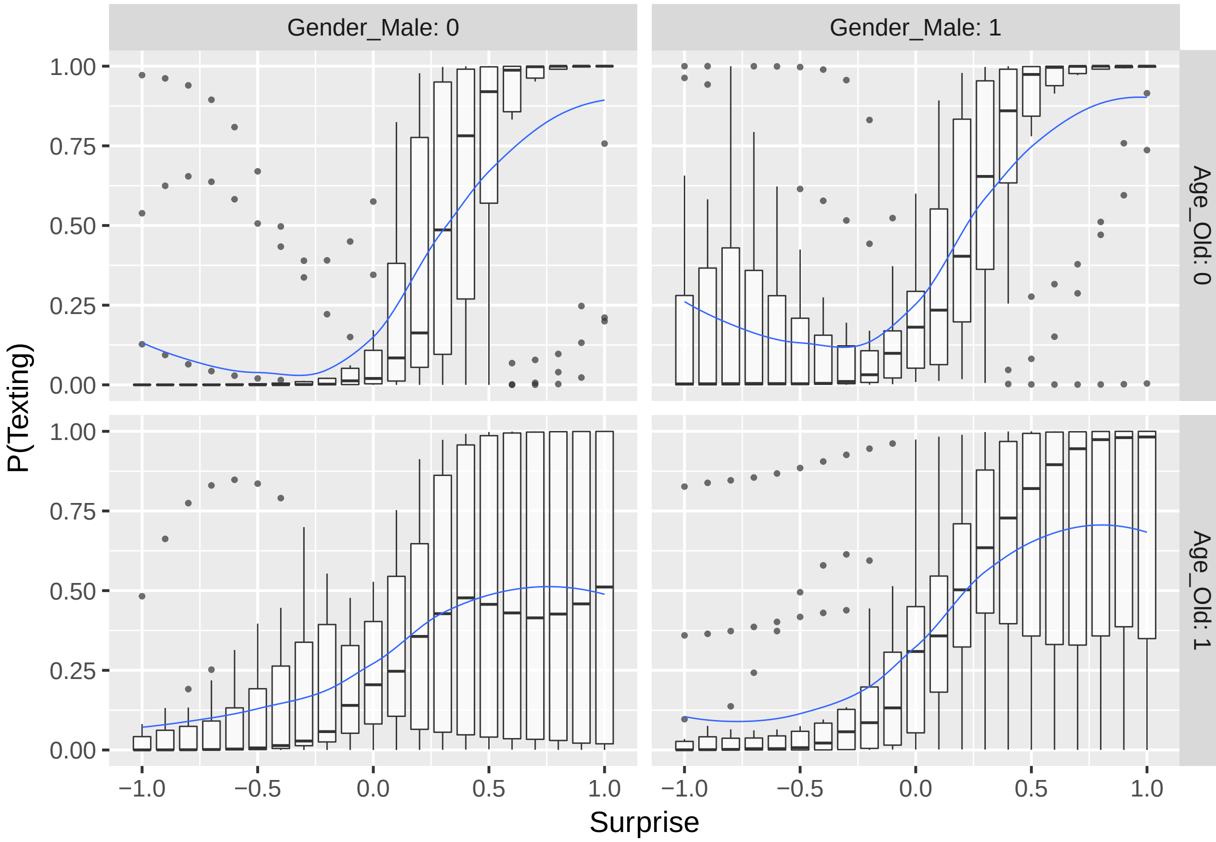


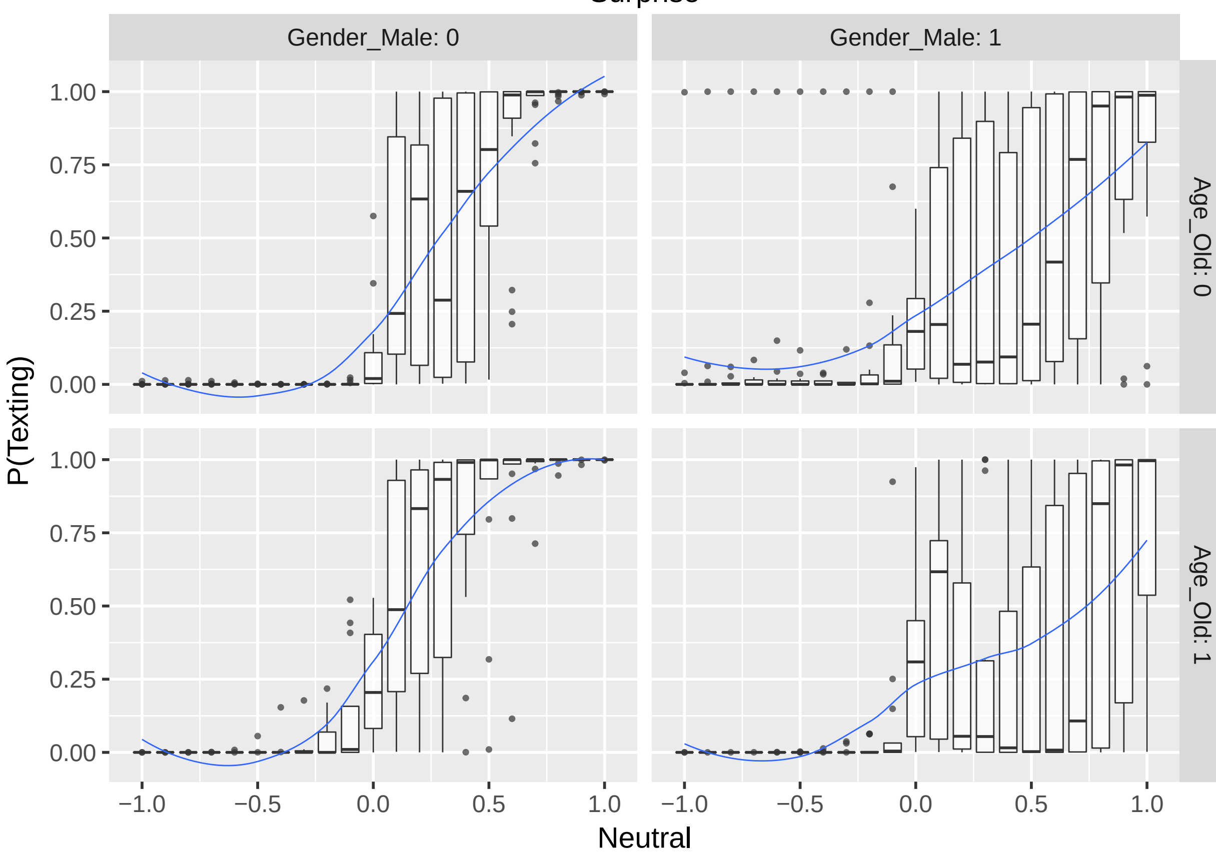

Gender_Male: 0
Gender_Male: 1
Age_Old: 0
Age_Old: 1
P(Texting)
1.00
0.75
0.50
0.25
0.00
−1.0
−0.5
0.0
0.5
1.0
Disgust


Gender_Male: 0
Gender_Male: 1
Age_Old: 0
Age_Old: 1
P(Texting)
1.00
0.75
0.50
0.25
0.00
−1.0
−0.5
0.0
0.5
1.0
Fear


Gender_Male: 0
Gender_Male: 1
Age_Old: 0
Age_Old: 1
P(Texting)
Joy


Gender_Male: 0
Gender_Male: 1
Age_Old: 0
Age_Old: 1
P(Texting)
Sad


Gender_Male: 0
Gender_Male: 1
Age_Old: 0
Age_Old: 1
P(Texting)
1.00
0.75
0.50
0.25
0.00
−1.0
−0.5
0.0
0.5
1.0
Surprise


Gender_Male: 0
Gender_Male: 1
Age_Old: 0
Age_Old: 1
P(Texting)
1.00
0.75
0.50
0.25
0.00
−1.0
−0.5
0.0
0.5
1.0
Neutral