

Case 2 Report: Detecting Stress Using Wearables

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1 Introduction

Stress can have disastrous long-term effects on the human body [1]. In fact, in 2015, the British Health and Safety Executive found that 37% of work-related illnesses were attributed to stress alone. One way to recognize and mitigate stress is through automated detection methods [2]. Existing wearable devices, which can be wrist or chest-worn, are able to gather relevant physiological data on wearers that can be used to predict their affective state (e.g. stress). As certain affective states, namely amusement, have similar physiological markers to stress, it is often a difficult task to discriminate between them.

This case study seeks to determine whether sensor data is useful in discriminating between stress and amusement conditions as well as understand the relationship between various physiological features and stress. It further aims to discover which types of sensor data are most useful in discriminating between amusement and stress—that is, can a model built from *only* wrist sensor data adequately detect stress, or is a combination of wrist and chest-worn sensor data considerably better? Finally, the study seeks to provide a quantification of heterogeneity across different individuals in the response to stress versus amusement. In order to address each of these objectives, we will use a database provided by Schmidt et al [2]. In section 2, we will provide a comprehensive overview of the data as well as describe our feature engineering process. Section 3 explores the efficacy of wrist-only versus combined sensor data in detecting stress and proposes a logistic regression model with principal components as inputs. Section 4 describes the heterogeneity in stress response among subjects in the study. Our final section discusses limitations and conclusions.

2 Data

2.1 Description of Data

A total of 17 individuals participated in the original study. However, due to sensor malfunction for two subjects, only data for 15 subjects was considered in our analysis [2]. Raw data was recorded by two sensor devices: the RespiBAN [3], which is chest worn, and the Empatica E4 [4], which is wrist worn. From the RespiBAN, the following modalities were measured for each individual at 700 Hz: *Electrocardiogram (ECG)*, *Electrodermal Activity (EDA)*, *Electromyogram (EMG)*, *Skin temperature (TEMP)*, and *3-axis accelerometry (ACC)*. From the Empatica E4, the following modalities were measured for each individual: *3-axis accelerometry (ACC, 32 Hz)*, *Blood Volume Pulse (BVP, 64 Hz)*, *Electrodermal Activity (EDA, 4 Hz)*, *Skin temperature (TEMP, 4 Hz)*, *Heart Rate (HR, 1 Hz)*.

ECG measurements record electrical signals in the heart, and are useful in monitoring heart health [5]. EMG measures muscle response to brain signals [6]. EDA is a measure of the neurally mediated effects on sweat gland permeability [7]. TEMP measures the skin's temperature, in which variability can be an indicator of stress [8]. ACC is used to record horizontal, vertical, and forward-backward acceleration of object movement. Studies have shown certain additional predictive power for stress detection can be gained by incorporating ACC data into the predictive model [9]. BVP measures the volume of blood that passes through tissues with each beat of the heart [10]. Finally, HR, or the number of heart beats per minute, has been found to vary empirically with affective state [11]. It is important to note that HR was not directly measured by the Empatica E4 device. Instead, the makers of the Empatica E4 use a proprietary algorithm to derive HR from BVP [12].

2.2 Feature Engineering

In order to combine data from the two sensors, we first downsampled each modality (barring heart rate) to 4 Hz. As heart rate was measured at 1 Hz, we repeated each HR value four times in order to provide a proxy for a 4 Hz measurement. Using the accelerometry data for the individual X, Y, and Z axes, we derived an additional measure, ACC 3D, representing the magnitude of total acceleration. We then proceeded to segment these sensor signals into window sizes of 5 seconds with 0.25 second shifts. Within each window the following features were engineered for each modality: *mean*, *standard deviation*, *minimum value*, and *maximum value*. We adapted this feature engineering process from [13]. As our study seeks to discriminate between stress and amusement, we filtered our data for only those observations in which the two states were observed. In our encoding, values of 0 corresponded to *amusement* and values of 1 corresponded to *stress*.

2.3 Exploratory Data Analysis

Fig. 1 Distribution of Mean Wrist EDA by State

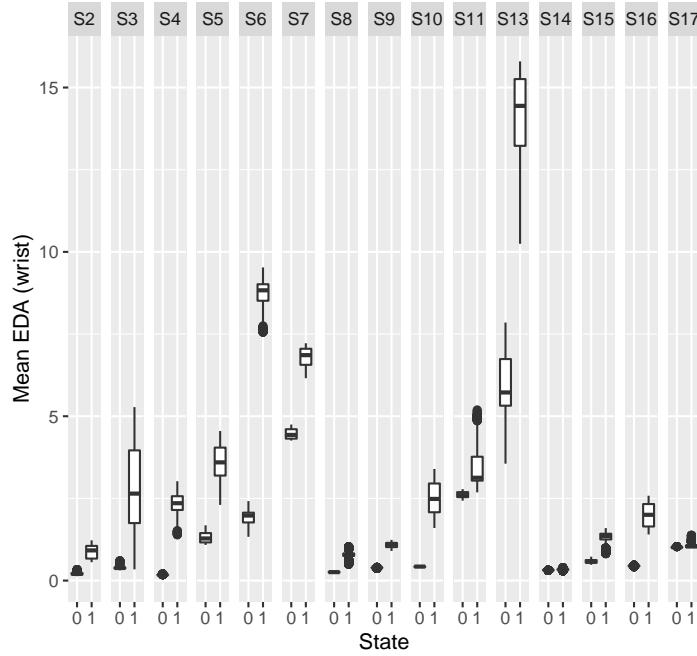
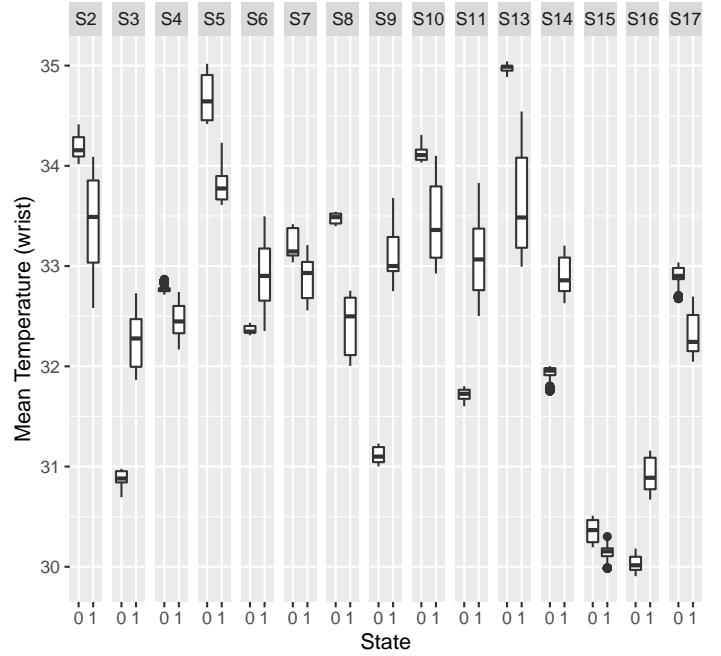


Fig. 2 Distribution of Mean Wrist Temperature by State



After examining boxplots of the distributions of various physiological measures by affective state (see A.1 for all plots of this type), the features that had the greatest difference in distribution between the two affective states and across the 15 subjects were *EDA_wrist_mean*, *Temp_wrist_mean*, and *hr_wrist_mu*. Figure 1 indicates that for all subjects, the mean EDA values are higher in the stressed state. For subjects 3, 5, 6, 7, 10, and 13, the difference in the distribution of mean EDA between the two states is more drastic than for the other subjects. Figure 2 shows that for some subjects, mean wrist temperature is higher in the stressed state. Conversely, other subjects' mean temperatue tends to be lower when stressed. This points to evidence of some heterogeneity in stress response. In addition, for certain subjects (such as subject 13), there is no overlap in the mean EDA values or mean wrist temperature values between the two states. This is likely to cause perfect separation in logistic regression (see Section 5 for a discussion of potential changes to the experimental design to deal with this issue).

Our correlation matrix (A.2) shows that high collinearity exists among engineered features. Collinearity among covariates can be dangerous in providing unreasonable coefficient estimates with inflated standard errors [14]. As one of our main objectives was to understand the relationship between certain physiological attributes and affective state, it was imperative that our model estimates were trustworthy. For this reason, domain driven insights were useful in selecting certain features to keep in the model, while omitting those contributing to greater multicollinearity. For example, features related to BVP and ECG measurements were ultimately excluded from our analysis due to their strong relationship with heart rate. As noted earlier, the Empatica E4 provides a measure of heart rate that is algorithmically derived from BVP [12]. Heart rate can similarly be derived from

ECG measurements [15]. Thus, in avoiding redundancy of information, BVP and ECG features were removed from the analysis, while those regarding HR remained. We further opted to remove the mean values of each accelerometry measurement (X, Y, Z, and 3D) over each of the five second windows. Our reasoning for excluding these features was due to our belief that variance in motion, which was captured by the standard deviation of accelerometry measurements in each window, would be more strongly associated with affective state than average accelerometry [16]. Finally, although we originally computed the minimum and maximum values for each physiological modality, we ultimately omitted these due to issues of underdispersion [17]. Specifically, our exploratory data analysis found that the minimum and maximum measurements across various modalities exhibited small variance. A.2 provides a concrete visualization of these low variances features.

3 Methods

3.1 Principal Component Analysis

After reducing the dimensionality of our feature space, we sought to determine the efficacy of the wrist sensor alone in discriminating between stress and amusement. For this purpose, we created two separate logistic regression models—one with data coming only from the wrist sensor, and the other with data coming from both wrist and chest sensors. In these two datasets, we continued to explore methods to reduce dimensionality and account for high correlation between covariates. Techniques such as stepwise variable selection and lasso regularization were considered, but were found ineffective. We ultimately settled on principal component analysis (PCA) as a means of reducing dimensionality and multicollinearity. Based on the scree plots found in A.3, we chose to utilize 4 components for both the wrist-only and combined data. For both, original features were normalized (mean-centered and standardized) before the extraction of principal components, as is recommended for PCA [18].

Our wrist data considered the following original features, before PCA was performed: Wrist ACC (X, Y, Z, and 3D) standard deviation, Wrist EDA standard deviation and mean, Wrist TEMP standard deviation and mean, and HR standard deviation and mean. Our combined wrist and chest data considered the following original features, before PCA was performed: Chest ACC (X, Y, Z, and 3D) standard deviation, EMG standard deviation and mean, Wrist EDA standard deviation and mean, Wrist TEMP standard deviation and mean, and HR standard deviation and mean.

Domain insights were useful in selecting which features to include from which sensors in the combined data model. For example, ACC measurements coming from the chest sensor were considered, as opposed to the wrist. This choice was motivated by Table 6 in Schmidt et. al [2], which shows the importance of ACC features derived from the chest sensor, but not wrist. The same table highlights the importance of TEMP and EDA related features coming from the wrist worn device, but not chest, warranting our inclusion of TEMP and EDA features coming from the wrist sensor in our combined data model. The other features for the combined data come from HR, which was only provided by the wrist-worn device, and EMG, which only comes from the chest-worn.

We then performed PCA for both the wrist only and combined data. The quality of representation plots (Fig. 3 and Fig. 4) show how much each feature contributes to each of the four components in the wrist-only and combined data models. Darker shades indicate a stronger contribution from a particular covariate to the principal component. As can be seen in the two plots, the resulting principal components are fairly interpretable. For example, for both data sets, standard deviations of ACC measurements contribute strongly to the first component. Thus, this component can be interpreted as a proxy for movement. Temperature and EDA are the main contributors to the second component, indicating that it represents information related to dermal temperature and activity (e.g. sweat). The third component clearly relates to heart rate, while the fourth differs slightly between two types of data. The fourth component for wrist only data pertains to variability in temperature, while that of the combined data pertains to neuro-muscular activity. We then fit two separate logistic regression models using the principal components extracted from the wrist-only and combined data, respectively.

Fig. 3 QoR Plot for Wrist PCA

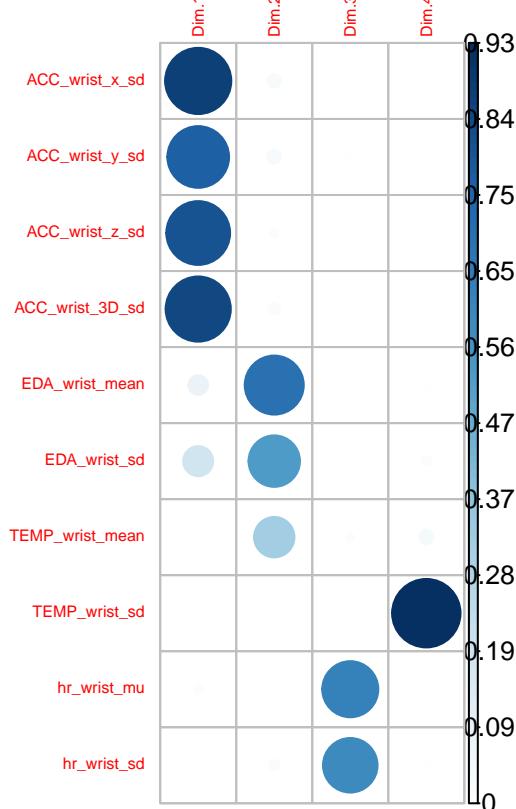


Fig. 4 QoR Plot for Combined Data PCA

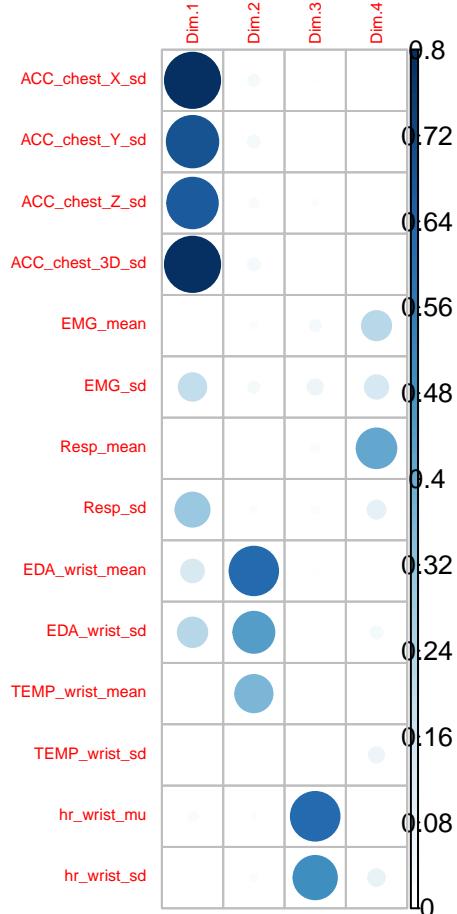


Table 1: Accuracy and F1 for Combined and Wrist Only Data Models

	Combined	Wrist
Accuracy	0.81	0.74
F1	0.73	0.59

Table 2: Confusion Matrices for Combined (top) and Wrist Only (bottom) Data Models

	Actual Amusement	Actual Stress
Predicted Amusement	15948	5238
Predicted Stress	6352	34626
	Actual Amusement	Actual Stress
Predicted Amusement	11608	5605
Predicted Stress	10692	34259

3.2 Model Evaluation

We then investigated the prediction accuracy and f1 scores of each logistic regression model using a 5-fold cross validation approach. In order to ensure that certain subjects were not over or underrepresented in the testing and training sets, we created stratified folds in which each individual’s representation was proportional to that of their representation in the entire dataset. As indicated in Table 1, the combined data model was shown to be superior in both accuracy and f1 score. A naive predictor would always choose 1 (the state that occurs more frequently in the data) and obtain an accuracy of 0.64. Both the combined data model and wrist-only data model have accuracies greater than 0.64. Therefore, we say that our models are useful in making effective predictions.

4 Results

We used the combined data model to understand the relationship between the various physioloigcal components and stress. From Table 3, we see that increases in variability of movement (Dim.1) and dermal temperature and activity (Dim.2) are associated with a multiplicative *increase* in the odds of stress. Conversely, increases in heart rate (Dim.3) and neuro-muscular activity (Dim.4) are associated with a multiplicative *decrease* in the odds of stress. Though it may seem “unnatural” that the odds of stress *decrease* with an increasing heart rate, research has found that anxiety has been linked to a slowing heart rate [19]. However, in order to determine if these trends are homogeneous, we added interaction effects between **subject** and each of the principal components to the existing combined data model. Here, **subject** represents the participant for which observed data pertains to. The output of the logistic regression model for combined data with interactions can be found in A.4.

Table 3: Estimate and Confidence Intervals for Coefficients in the Combined Data Model

	Estimate	2.5%	97.5%
(Intercept)	1.12	1.09	1.14
Motion	1.02	1.00	1.04
Dermal Temp and Activity	0.34	0.31	0.36
Heart Rate	-0.34	-0.36	-0.32
Neuro-Muscular Activity	-0.28	-0.30	-0.25

Fig. 5 Marginal Effects of Motion

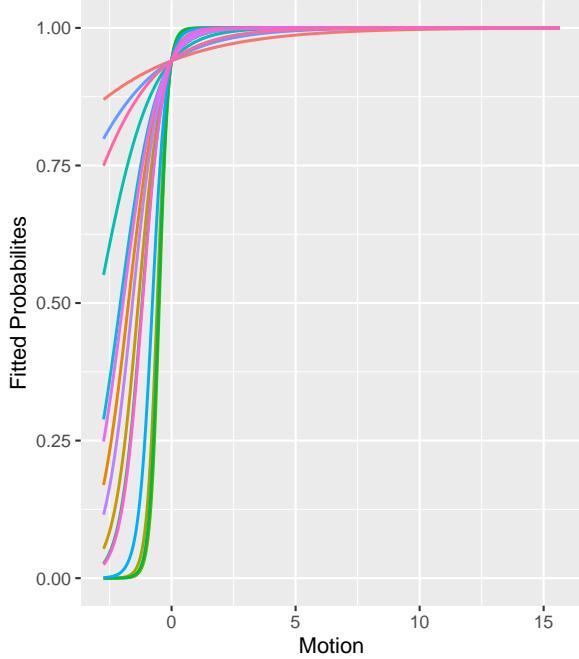


Fig. 6 Marginal Effects of Dermal Temp and Activity

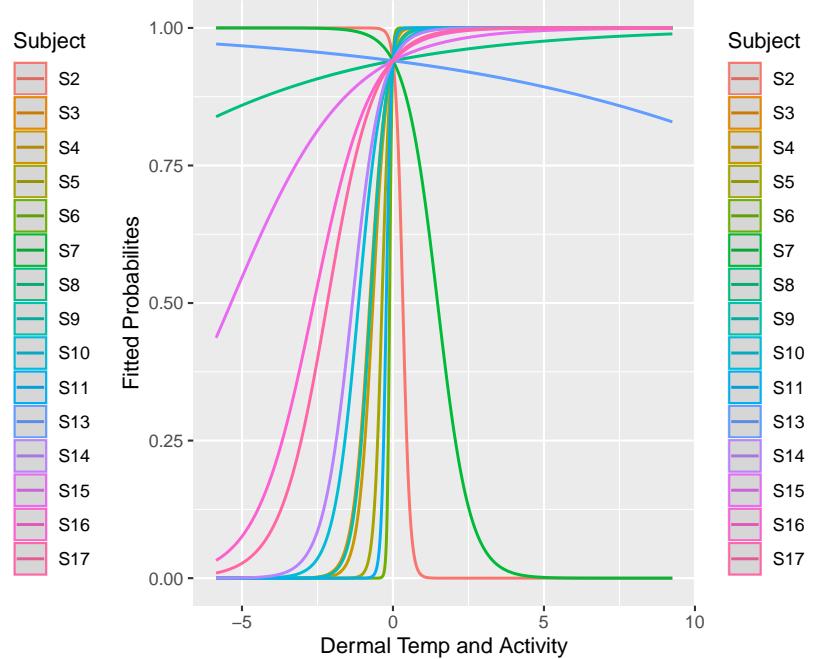


Fig. 7 Marginal Effects of Heart Rate

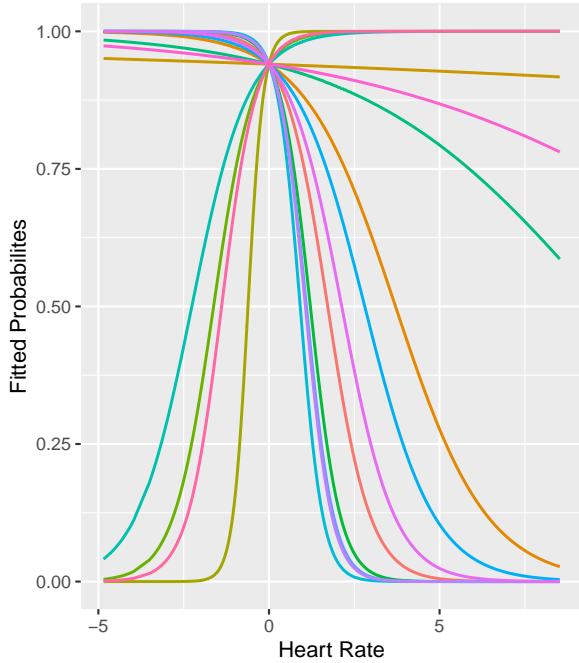
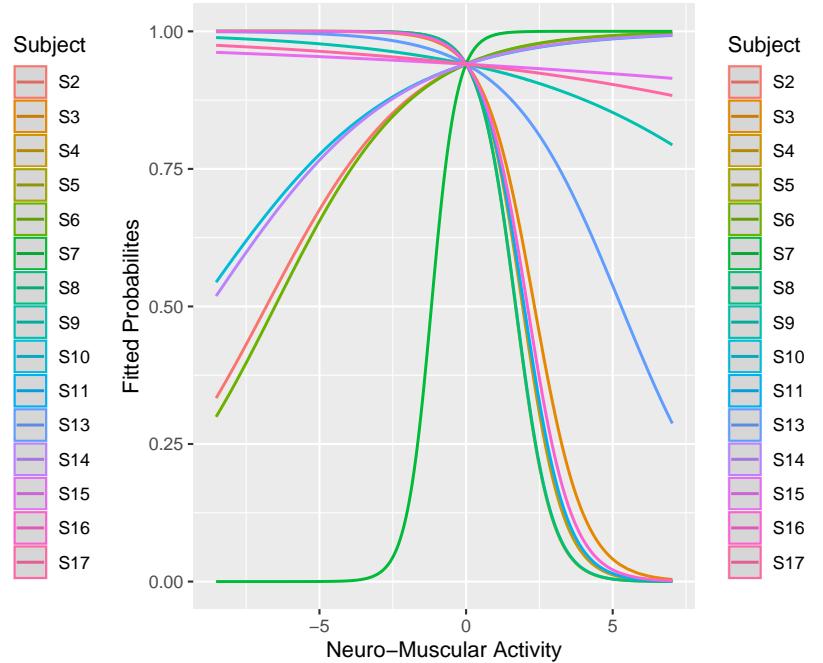


Fig. 8 Marginal Effects of Neuro-Muscular Activity



Figures 5 through 8 show the fitted probability of stress against each principal component, with different colors representing different subjects. From figure 5, we see that as the variation in motion (Dim.1) increases, the probability of stress increases similarly for all subjects, except for subjects 13 and 2. We note that for subjects 13 and 2, as the variability of motion increases, the probability of stress increases at a slower rate than other subjects. However, all subjects exhibit an increasing trend. Figure 6 shows that as the variation in mean dermal temperature and activity increases (Dim.2) increases, the probability of stress increases similarly for all subjects except for subjects 2, 7, and 13. For these three subjects, the probabilities decrease.

Figure 7 shows that as heart rate (Dim.3) increases, the probability of stress decreases similarly for all subjects except for subjects 5, 6, 9, and 17. For these four subjects, the probabilities increase. Figure 8 shows that as neurological and muscular activity (Dim.4) increase, the probability of stress decreases similarly for all subjects barring subjects 2, 6, 7, 10, and 14. For these five subjects, as neuro-muscular activity increases, the probability of stress increases as well.

Table 4: Accuracy and f1 for Final Model

	Accuracy	F1
Final Model	0.9	0.86

Table 5: Confusion Matrix for Final Model

	Actual Amusement	Actual Stress
Predicted Amusement	18545	2263
Predicted Stress	3755	37601

These behaviors can be corroborated by the coefficient estimates in A.4. When adding together the main effect of a principal component and its interaction with a particular subject, it can be noted that positive values correspond with an increasing trend in the above plots. Conversely, negative values correspond with a decreasing trend. This is consistent with the notion that positive coefficients in logistic regression indicate a multiplicative increase in the odds of an outcome, while negative coefficients signify a decrease.

Fig. 9 ROC Plot for Final Model

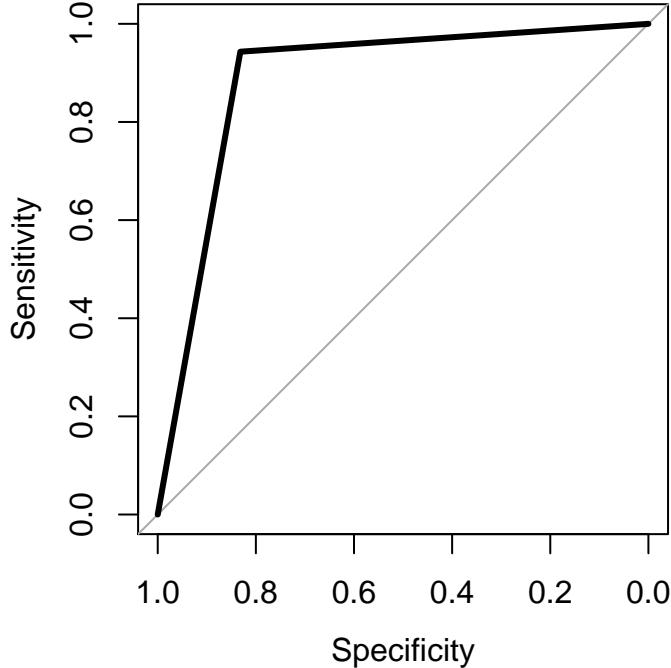


Table 4 shows the accuracy and f1 scores of the combined data model with subject interactions. These metrics were computed using the same 5-fold cross validation approach described in Section 3.2. The ROC curve in figure 9 shows that our final model discriminates moderately well between the stress and amusement states. Specifically, the area under the curve is 0.89.

5 Conclusions and Limitations

In conclusion, sensor data *is* useful in discriminating between stress and amusement conditions. While using wrist-only data yielded an accuracy comparable to that of using both types of sensor data, the f1 score indicates that using sensor data in combination is more useful in discriminating between the two states. It appears that greater variability in movement and dermal activity (e.g. sweat) are related to a higher likelihood of stress, whereas greater heart rate and neuro-muscular activity are related to a lower likelihood of stress. Adding interaction effects between the 15 subjects and the physiological components shows that these trends are not

homogenous, however. For instance, for some subjects, as heart rate increases, so does the probability of stress. Although we ultimately proposed a model that was effective in discriminating between stress and amusement, there were some inherent limitations to the dataset in use. Firstly, we encountered the issue of perfect separation when including the subject covariate in the model proposed in section 4. There are various possible explanations for this. As mentioned in the exploratory data analysis section, it is possible that for certain subjects, mean EDA wrist measurement is always above a certain threshold when stressed (and, consequently, below when amused). In addition, it is important to note that in the experimental design of Schmidt et al [2], the amusement condition was derived from watching a movie while the stress condition was induced by public speaking. There may be some flaws in this design. For example, people may not sweat while watching a movie (as barely any physical movement is involved) but tend to do so when speaking in front of others (due to movement and anxiety). One potential modification to the experimental design of Schmidt et al would be for both amusement and stress conditions to involve the same amount of physical activity—watching a comedy for amusement versus watching a thriller for stress, for example. New data from such an experiment could mitigate this issue of perfect separation. Yet another limitation to the dataset was the small sample size of 15 subjects. In future studies, more subjects would be ideal in gaining a more holistic understanding of heterogeneity that exists in stress response.

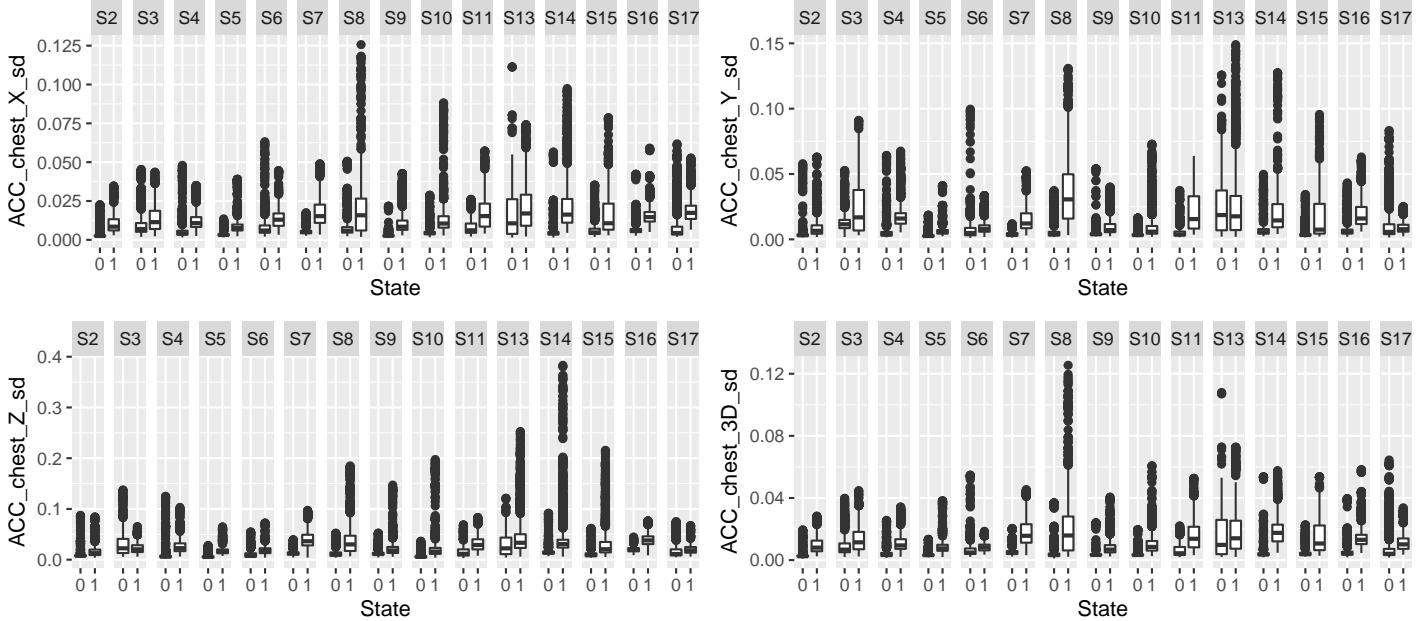
6 References

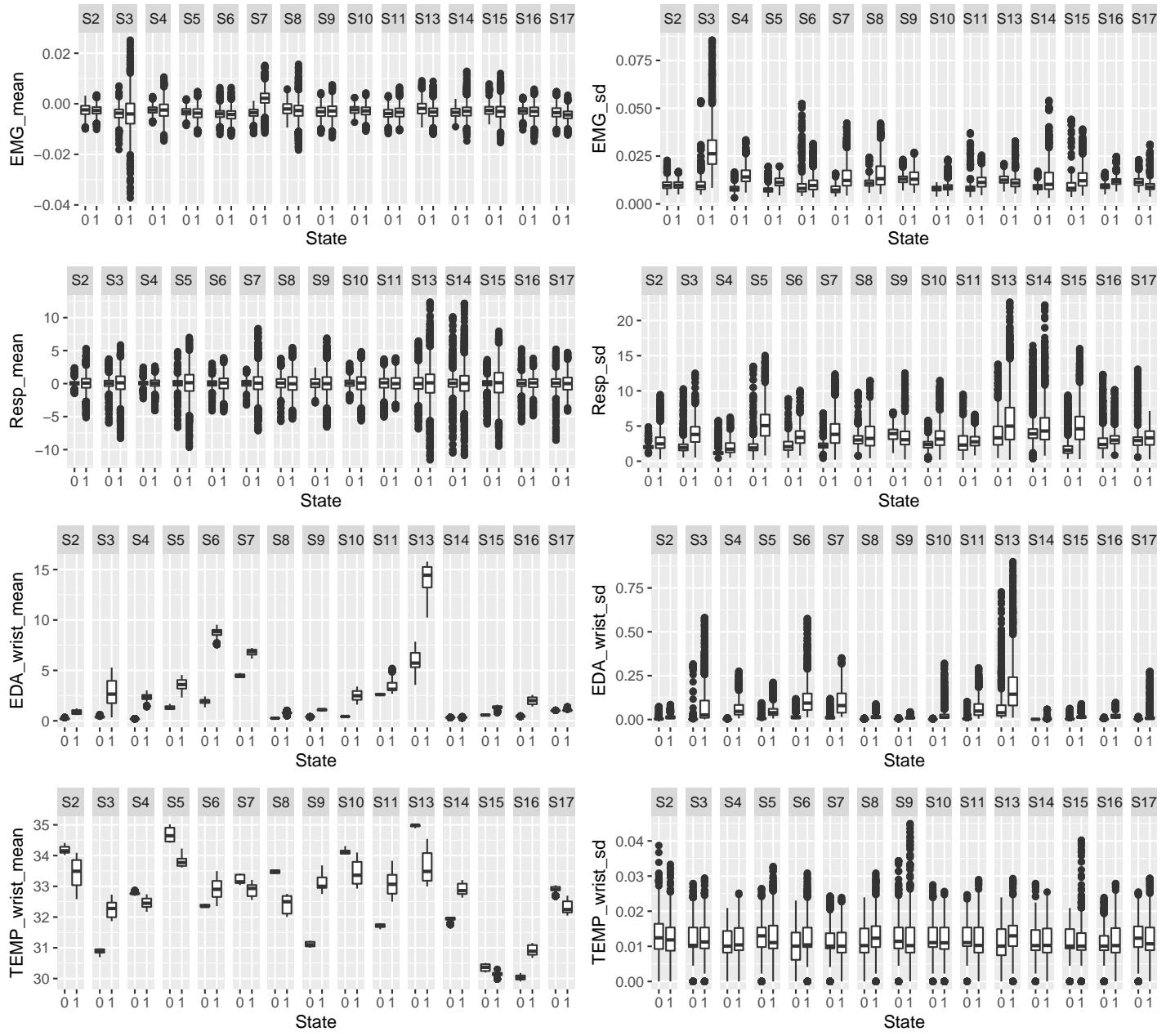
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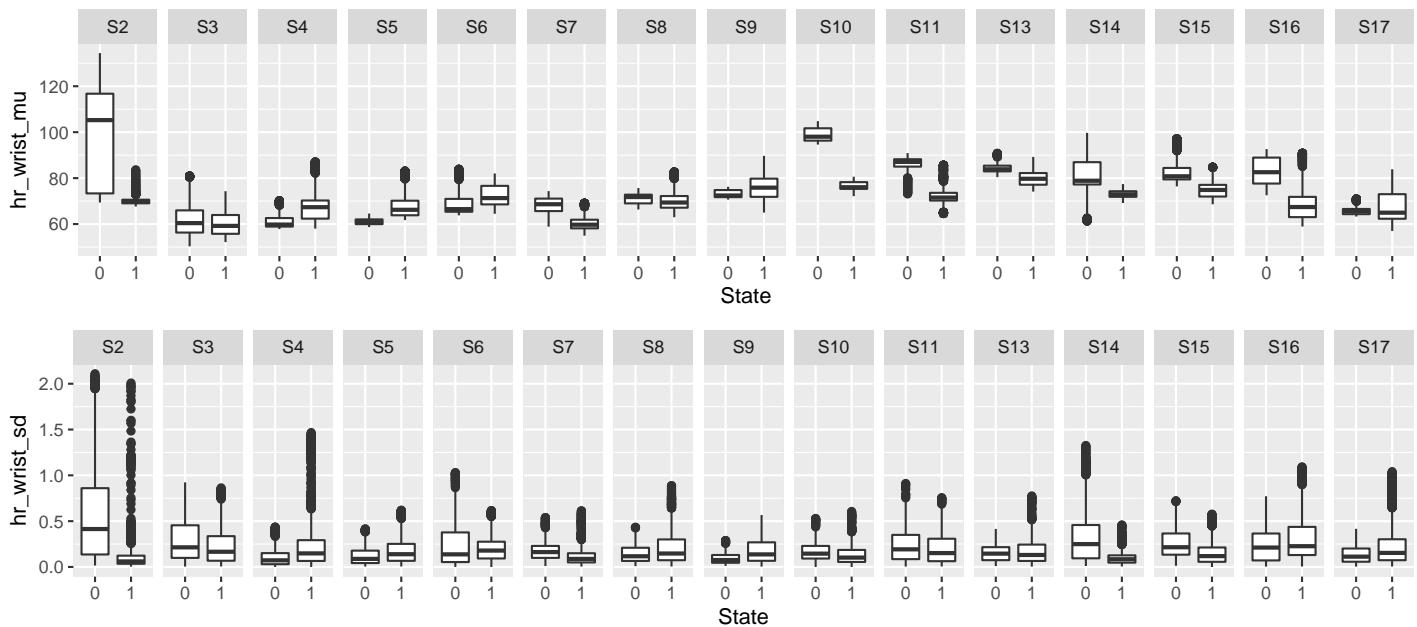
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7 Appendix

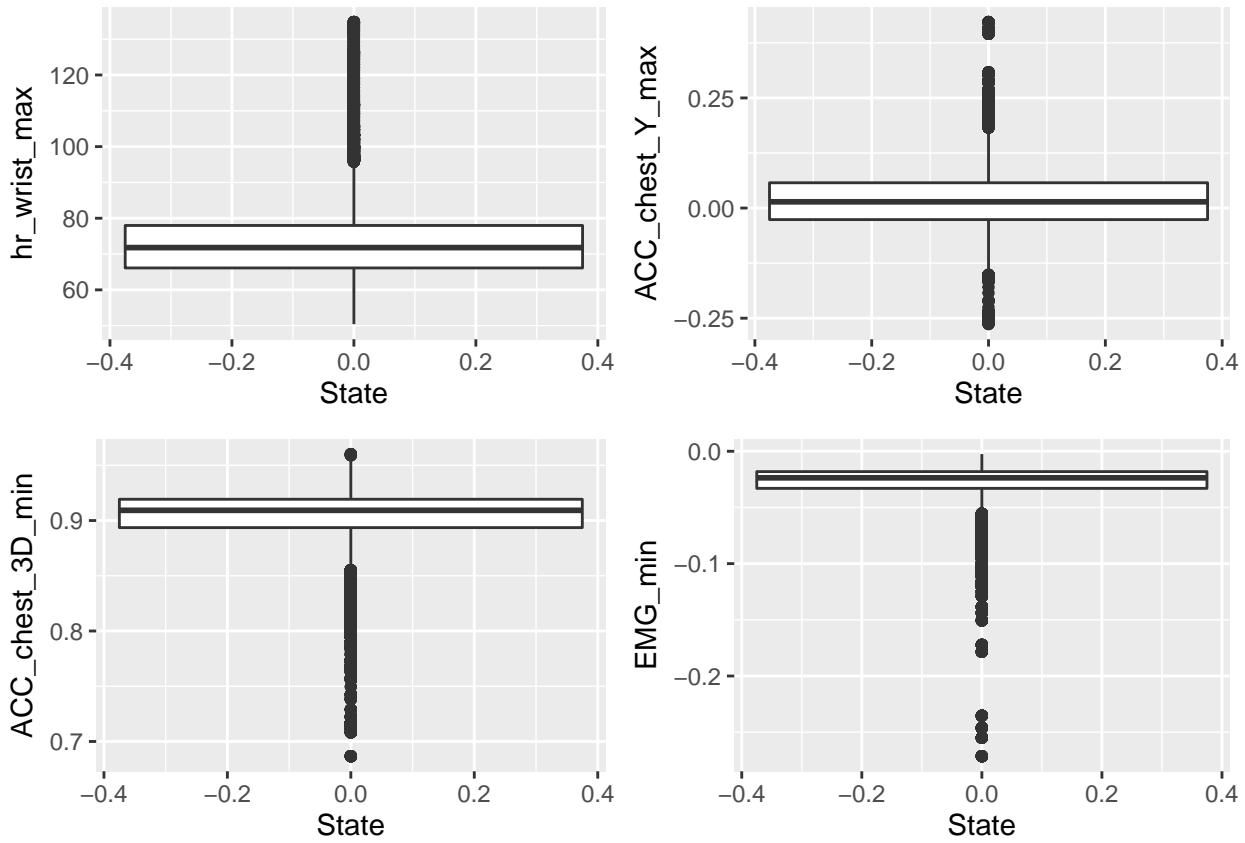
7.1 A.1





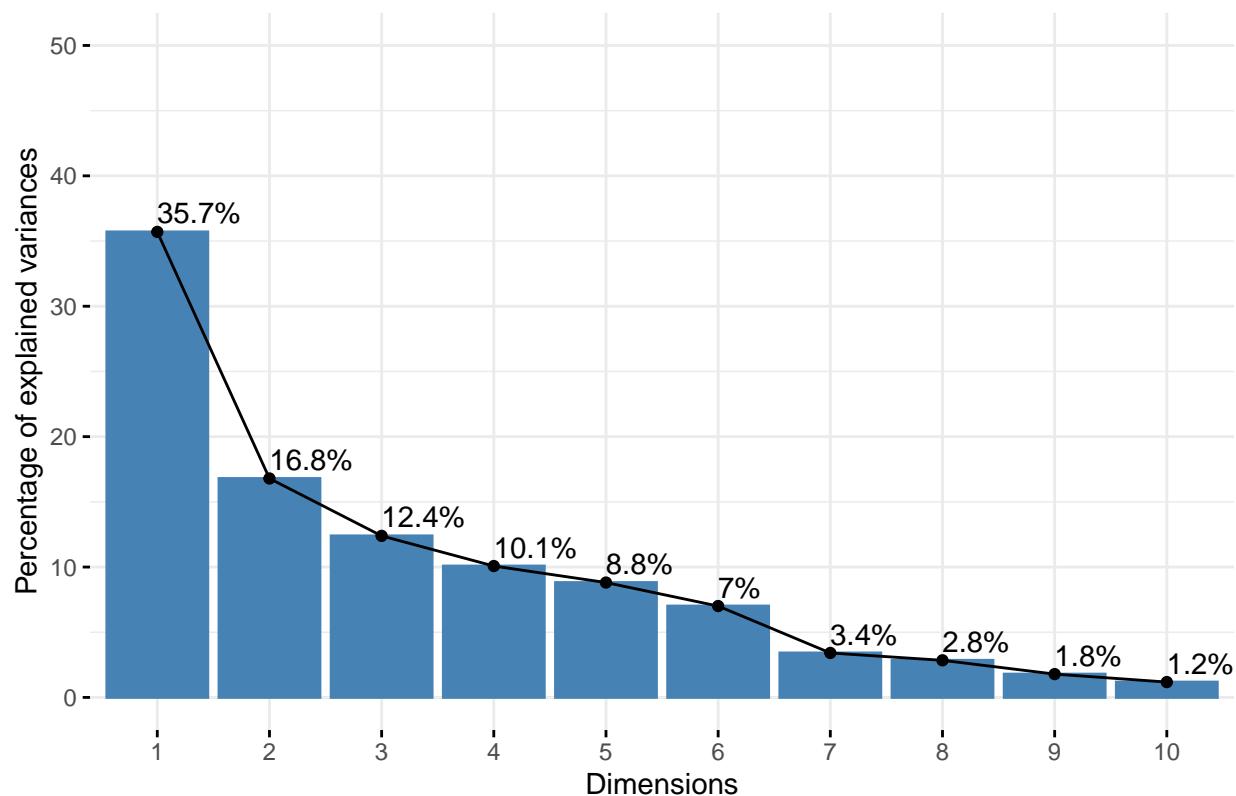


7.2 A.2

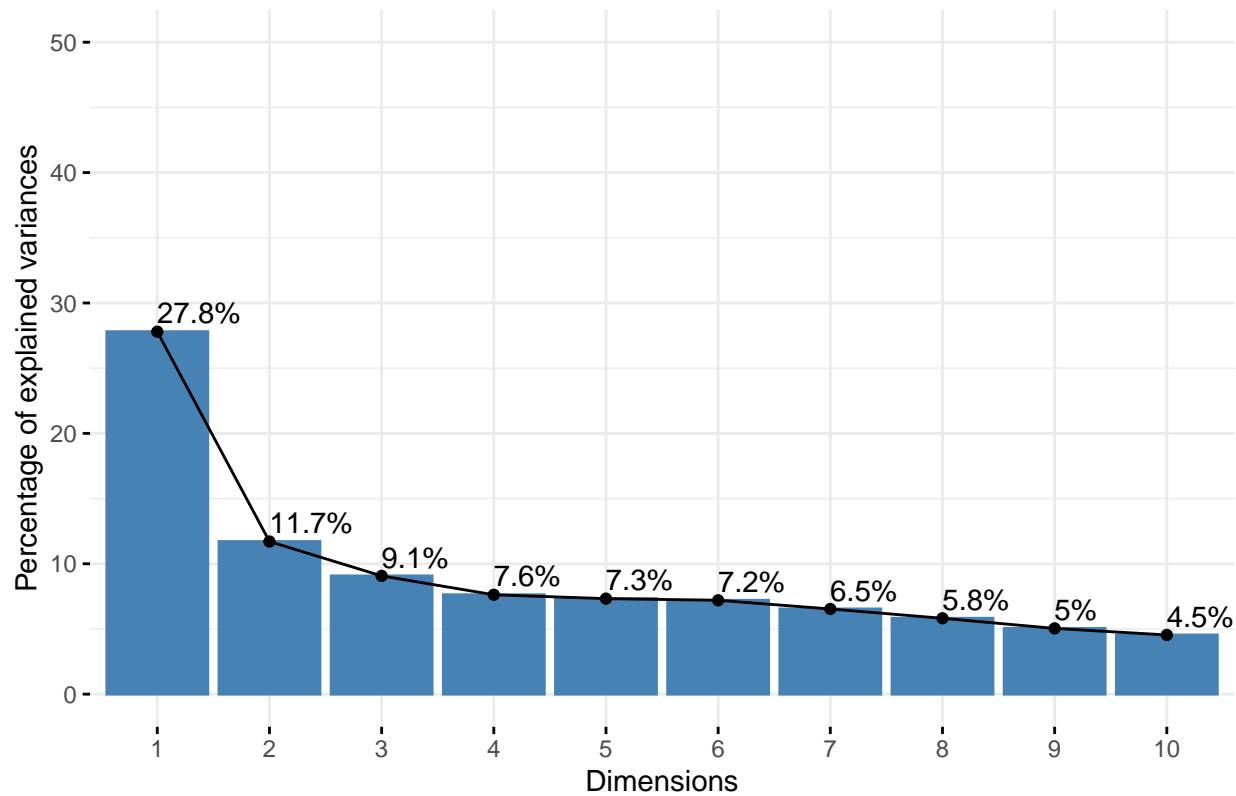


7.3 A.3

Scree Plot for Wrist Only Data



Scree Plot for Combined Data



7.4 A.4

##

```

## Call:
## glm(formula = Label ~ Dim.1 + Dim.2 + Dim.3 + Dim.4 + Dim.1:Subject +
##       Dim.2:Subject + Dim.3:Subject + Dim.4:Subject, family = binomial(link = "logit"),
##       data = pca_vals)
##
## Deviance Residuals:
##    Min      1Q  Median      3Q     Max 
## -4.6026 -0.2067  0.0238  0.4043  3.1446 
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)    
## (Intercept) 2.75764   0.04035 68.345 < 2e-16 ***
## Dim.1        0.31351   0.08606  3.643 0.000270 ***  
## Dim.2       -8.43530   0.41164 -20.492 < 2e-16 ***  
## Dim.3       -1.60165   0.07041 -22.746 < 2e-16 ***  
## Dim.4        0.40475   0.08485  4.770 1.84e-06 ***  
## Dim.1:SubjectS3 1.27153   0.09933 12.801 < 2e-16 ***  
## Dim.1:SubjectS4 1.74004   0.09940 17.506 < 2e-16 ***  
## Dim.1:SubjectS5 4.43791   0.20646 21.495 < 2e-16 ***  
## Dim.1:SubjectS6 5.26245   0.36695 14.341 < 2e-16 ***  
## Dim.1:SubjectS7 5.00461   0.22440 22.302 < 2e-16 ***  
## Dim.1:SubjectS8 1.99914   0.09962 20.069 < 2e-16 ***  
## Dim.1:SubjectS9 0.61708   0.09100  6.781 1.19e-11 ***  
## Dim.1:SubjectS10 1.02093   0.10497  9.726 < 2e-16 ***  
## Dim.1:SubjectS11 3.25439   0.20597 15.801 < 2e-16 ***  
## Dim.1:SubjectS13 0.18959   0.08811  2.152 0.031420 *  
## Dim.1:SubjectS14 1.43407   0.09598 14.942 < 2e-16 ***  
## Dim.1:SubjectS15 1.09561   0.09425 11.624 < 2e-16 ***  
## Dim.1:SubjectS16 2.03518   0.11104 18.328 < 2e-16 ***  
## Dim.1:SubjectS17 0.29241   0.09340  3.131 0.001745 **  
## Dim.2:SubjectS3 12.02063   0.41988 28.629 < 2e-16 ***  
## Dim.2:SubjectS4 12.58803   0.43595 28.875 < 2e-16 ***  
## Dim.2:SubjectS5 16.02306   0.60414 26.522 < 2e-16 ***  
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## Dim.3:SubjectS3 0.85803   0.10300  8.331 < 2e-16 ***  
## Dim.3:SubjectS4 1.56018   0.09992 15.615 < 2e-16 ***  
## Dim.3:SubjectS5 6.08450   0.28912 21.045 < 2e-16 ***  
## Dim.3:SubjectS6 3.30071   0.32375 10.195 < 2e-16 ***  
## Dim.3:SubjectS7 -0.67064   0.23745 -2.824 0.004738 **  
## Dim.3:SubjectS8 1.31896   0.13318  9.904 < 2e-16 ***  
## Dim.3:SubjectS9 2.82131   0.11328 24.906 < 2e-16 ***  
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## Dim.3:SubjectS11  0.61919    0.18121   3.417 0.000633 ***
## Dim.3:SubjectS13 -0.91241    0.10440  -8.740 < 2e-16 ***
## Dim.3:SubjectS14 -0.97794    0.15333  -6.378 1.79e-10 ***
## Dim.3:SubjectS15  0.30891    0.10075   3.066 0.002169 **
## Dim.3:SubjectS16  1.42710    0.09288  15.365 < 2e-16 ***
## Dim.3:SubjectS17  3.58877    0.10381  34.572 < 2e-16 ***
## Dim.4:SubjectS3  -1.58708    0.10145 -15.644 < 2e-16 ***
## Dim.4:SubjectS4  -1.83509    0.12602 -14.562 < 2e-16 ***
## Dim.4:SubjectS5  -2.03910    0.16427 -12.413 < 2e-16 ***
## Dim.4:SubjectS6   0.01843    0.43488   0.042 0.966200
## Dim.4:SubjectS7   1.92784    0.26413   7.299 2.90e-13 ***
## Dim.4:SubjectS8  -2.03017    0.11333 -17.914 < 2e-16 ***
## Dim.4:SubjectS9  -0.60533    0.09967  -6.073 1.25e-09 ***
## Dim.4:SubjectS10 -0.10198    0.11314  -0.901 0.367421
## Dim.4:SubjectS11 -1.79669    0.17621 -10.196 < 2e-16 ***
## Dim.4:SubjectS13 -0.92594    0.09385  -9.866 < 2e-16 ***
## Dim.4:SubjectS14 -0.09012    0.10881  -0.828 0.407515
## Dim.4:SubjectS15 -0.45976    0.09844  -4.670 3.01e-06 ***
## Dim.4:SubjectS16 -1.72068    0.12083 -14.240 < 2e-16 ***
## Dim.4:SubjectS17 -0.50899    0.09819  -5.184 2.18e-07 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 81147  on 62163  degrees of freedom
## Residual deviance: 31344  on 62103  degrees of freedom
## AIC: 31466
##
## Number of Fisher Scoring iterations: 12

```