Case 2 Report: Detecting Stress Using Wearables

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```
features_all_modalities = function(fn, win_size, shift) {
  df_all = read.csv(fn) %>%
    mutate(ACC_chest_3D = sqrt(ACC_chest_X^2+ACC_chest_Y^2+ACC_chest_Z^2)) %>%
    mutate(ACC_wrist_3D = sqrt(ACC_wrist_x^2+ACC_wrist_y^2+ACC_wrist_z^2))
  drops <- c("X", "Label", "subject")
  df = df_all[ , !(names(df_all) %in% drops)]
  replace_rows =  length(rollapply(df[,1], width = win_size*4, by = shift, FUN = mean, align = "left
  features_df <- data.frame(matrix(ncol = ncol(df)*4, nrow = replace_rows))
  new_names = sapply(1:length(df), function(c) {
    c(paste0(colnames(df)[c],"_mean"),
      paste0(colnames(df)[c],"_sd"),
      #paste0(colnames(df)[c],"_range"),
      paste0(colnames(df)[c],"_min"),
      paste0(colnames(df)[c],"_max")
      # paste0(colnames(df)[c],"_skew")
      )
  })
  colnames(features_df) = new_names



  for (c in 1:length(df)) {

    # finding mu
    mu_vals = rollapply(df[,c], width = win_size*4, by = shift, FUN = mean, align = "left")
    new_col_name = paste0(colnames(df)[c],"_mean")
    cindx = which(colnames(features_df)==new_col_name)
    features_df[, cindx] = mu_vals

    # finding sd
    sd_vals = rollapply(df[,c], width = win_size*4, by = shift, FUN = var, align = "left")
    new_col_name = paste0(colnames(df)[c],"_sd")
    cindx = which(colnames(features_df)==new_col_name)
    features_df[, cindx] = sqrt(sd_vals)

    # finding max
    max_vals = rollapply(df[,c], width = win_size*4, by = shift, FUN = max, align = "left")
    new_col_name = paste0(colnames(df)[c],"_max")
    cindx = which(colnames(features_df)==new_col_name)
    features_df[, cindx] = max_vals

    # finding min
```

```
    min_vals = rollapply(df[,c], width = win_size*4, by = shift, FUN = min, align = "left")
    new_col_name = paste0(colnames(df)[c],"_min")
    cindx = which(colnames(features_df)==new_col_name)
    features_df[, cindx] = min_vals

  }

 # make sure merge label, subject back into feature dataframe
  features_df$Label = df_all[1:replace_rows, "Label"]
  features_df$Subject = df_all[1:replace_rows, "subject"]
  return(features_df)
}
```

```
HR_calc = function(df, win_size, shift) {
  df <- df[rep(seq_len(nrow(df)), each = 4), ]
  mu_vals = rollapply(df, width = win_size*4, by = shift, FUN = mean, align = "left")
  sd_vals = rollapply(df, width = win_size*4, by = shift, FUN = sd, align = "left")
  min_vals = rollapply(df, width = win_size*4, by = shift, FUN = min, align = "left")
  max_vals = rollapply(df, width = win_size*4, by = shift, FUN = max, align = "left")

  return(list(mu = mu_vals, sd = sd_vals,
              min = min_vals, max = max_vals))
}
```

```
file_list <- list.files()
subject_data = file_list[grepl("df_S", file_list, fixed = TRUE)]
```

```
ALL_df = NULL
for (i in 1:length(subject_data)) {
  print(i)
  feature_data = features_all_modalities(subject_data[i], 5, 1) #CHANGE FILE PATH
  subject_no = gsub("\\..*","", sub('.*_', '', subject_data[i]))
  HR_fn = paste0("~/case-study-2/WESAD/", subject_no, "/", subject_no, "_E4_Data/HR.csv") #CHANGE F
  HR_data = read.csv(HR_fn)[-1,]
  hr = HR_calc(as.data.frame(HR_data), 5, 1)

  df_hr = data.frame(matrix(unlist(hr), nrow= length(hr$mu),
                            ncol=4, byrow = F))
  colnames(df_hr) = c("hr_wrist_mu","hr_wrist_sd", "hr_wrist_min", "hr_wrist_max")#, "hr_wrist_rang
  df_hr$ID =seq.int(nrow(df_hr))

  feature_data = feature_data[-c(1:40),]
  feature_data$ID <- seq.int(nrow(feature_data))

  S_df = merge(feature_data, df_hr, by="ID")
  ALL_df = rbind(ALL_df, S_df)
}
ALL_df = ALL_df %>% filter(Label %in% c("2","3"))
write.csv(ALL_df, "master_df.csv")
```

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. Statistical methods can then be applied to construct a mapping from observed sensor data to the wearer's 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 **, we will provide a comprehensive overview of the data as well as describe our feature engineering process. Section** explores the efficacy of wrist-only versus combined sensor data in detecting stress and proposes a logistic regression model with principal components as features. Section ___ 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. 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` for the chest measures muscle response to brain signals [6]. `EDA` for both wrist and chest are measures of 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` for both wrist and chest 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, but was instead derived from the BVP measure using a proprietary algorithm [12].

2.2 Feature Engineering

In order to combine each of the modalities from the two sensors, we first downsampled each modality (barring heart rate) to 4 Hz. As heart rate was recorded only once per second, we repeated each value four times in order to provide a proxy for a 4 Hz measurement. Using the accelerometer 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]. Finally, 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.

2.3 Exploratory Data Analysis

Fig. 2 Distribution of Mean Wrist EDA by State for All Sub

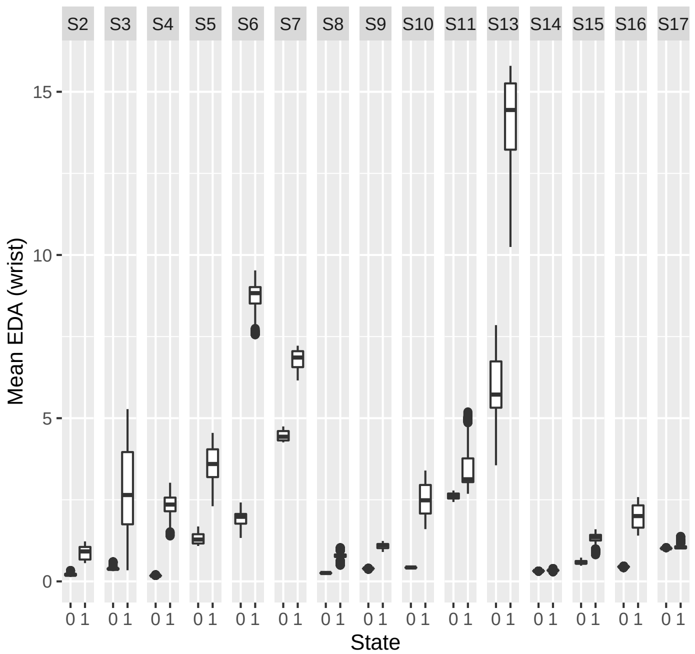
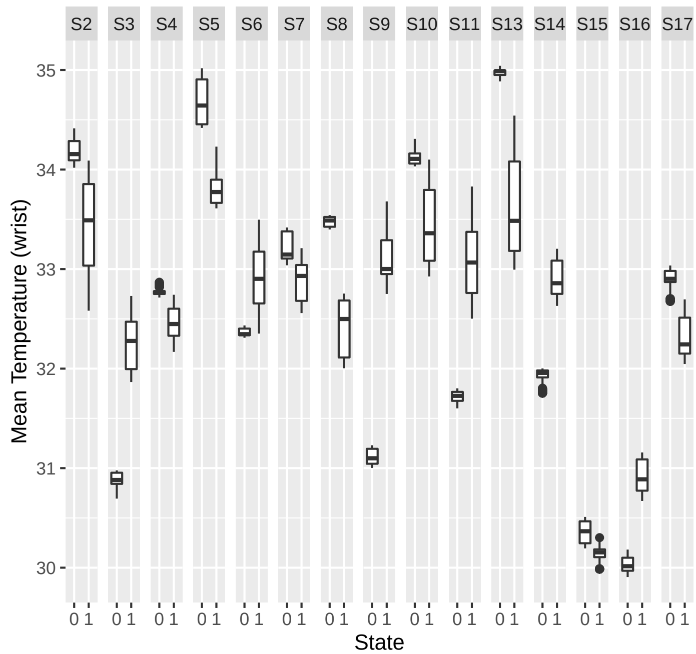


Fig. 3 Distribution of Mean Wrist Temperature by State fo



After examining boxplots of the distribution of physiological measures by state for each subject (see A.1 for all plots of this type), the variables that had the greatest difference in distribution between states and across subjects were `EDA_wrist_mean`, `Temp_wrist_mean`, and `hr_wrist_mu`. Figure 2 indicates that for all subjects, mean EDA values are higher in the stressed state. For subjects 3, 5, 6, 7, 10, and 13, the difference in the distribution of EDA between the two states is more drastic than that of the other subjects. Figure 3 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, pointing to heterogeneity in stress response. In addition, it is important to note that for certain subjects (such as subject 13), there is no overlap in mean EDA values or mean wrist temperature values between the two states. This is likely to cause perfect separation in logistic regression (see Conclusion for a discussion on potential changes to the experimental design to deal with this issue).

From our correlation matrix (A.2), we see 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 is to understand the relationship between certain physiological attributes and affective state, it is imperative that model estimates are 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`. 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 heart rate 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 covariates was due to our belief that variance in motion, which was captured by the standard deviation of accelerometry measurements in each window, is more strongly associated with affective state than average motion [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.3 provides a concrete visualization of these low variances features.

3 Methods

3.1 Model Selection

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 to reduce dimensionality such as stepwise variable selection and lasso regularization were considered, but were found ineffective (see A.4). In both the wrist-only and combined data models, we ultimately settled on principal component analysis (PCA) as a means of reducing dimensionality and multicollinearity. Based on figures in A.5, we chose to utilize 4 components in both models. For both wrist-only and combined data, 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 * `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 * `HR`: standard deviation and mean

In the combined data, `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 (A.5) 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` features 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, showing that it represents information related to dermal temperature and activity (e.g. sweat). The third component relates to heart rate, while the fourth differ slightly between two types of data: the component for wrist only data pertains to variability in temperature, whereas that for the combined data pertains to neuro-muscular activity. We fit two separate logistic regression models using the principal components extracted from the wrist-only and combined data, respectively.

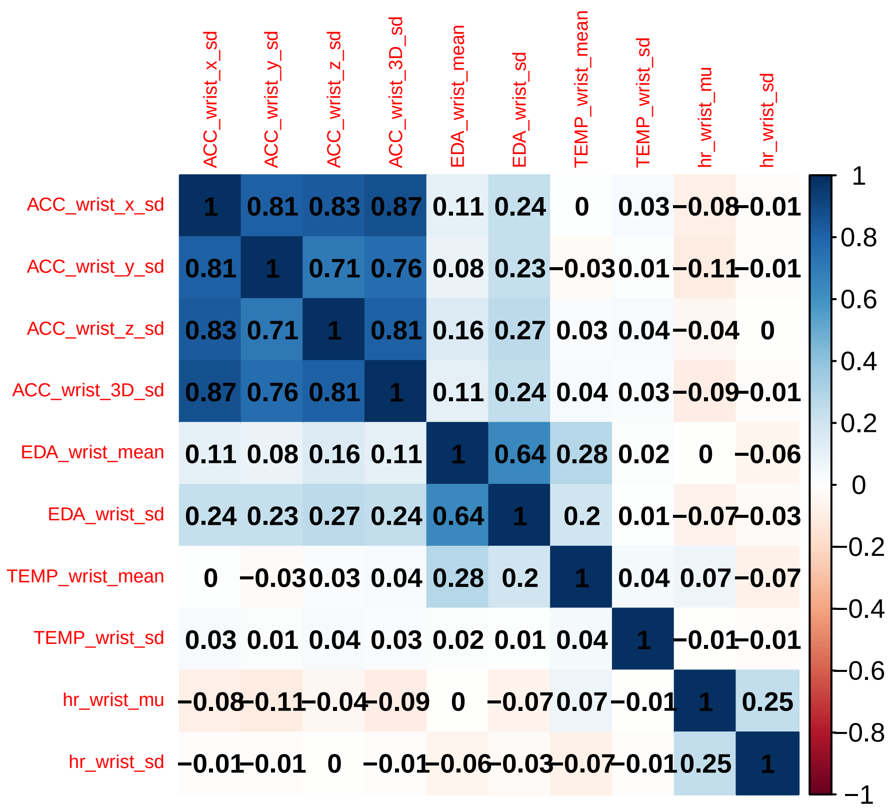
Table 1: Accuracy and F1 for All Data and Wrist Models

	All	Wrist
Accuracy	0.81	0.74
F1	0.73	0.59

Table 2: Confusion Matrices for All Data (left) and Wrist (right) 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

. 5 Correlation Matrix of Engineered Features (Wrist Oı



3.2 Model Evaluation

```
## `summarise()` ungrouping output (override with `.groups` argument)
## `summarise()` ungrouping output (override with `.groups` argument)
## `summarise()` ungrouping output (override with `.groups` argument)
## `summarise()` ungrouping output (override with `.groups` argument)
```

We then investigated the prediction accuracy and f1 scores of each 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 ___, the combined data model was shown to be superior in both

Table 3: Confusion Matrix for Final Model

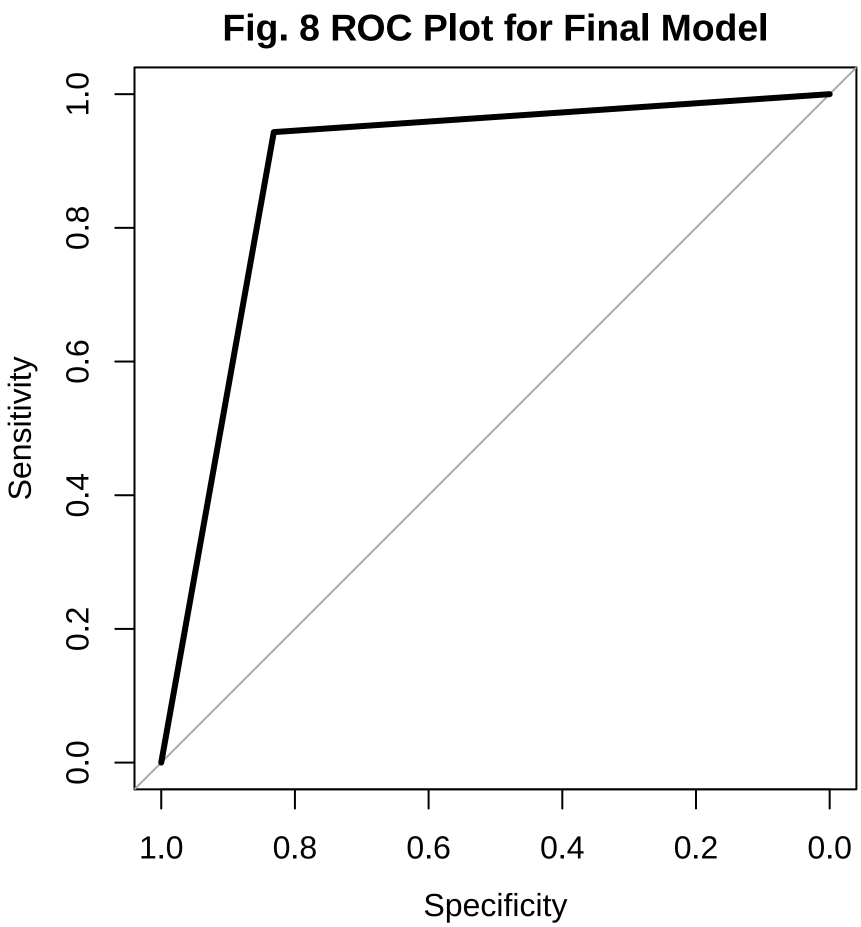
	Actual Amusement	Actual Stress
Predicted Amusement	11608	5605
Predicted Stress	10692	34259

accuracy and f1 score.

4 Results

```
## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
```




```
## Warning in RColorBrewer::brewer.pal(n, pal): n too large, allowed maximum for palette Set1 is 9
## Returning the palette you asked for with that many colors
```

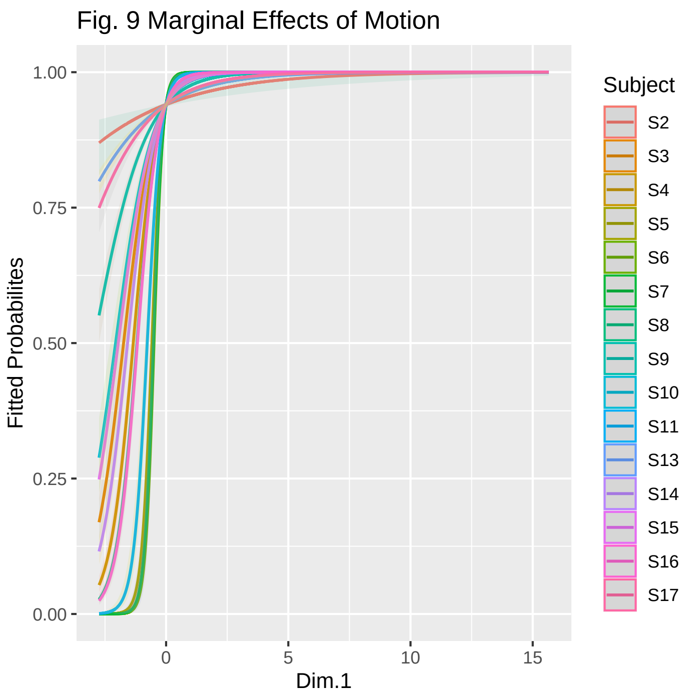
```
## Scale for 'colour' is already present. Adding another scale for 'colour',
## which will replace the existing scale.
```

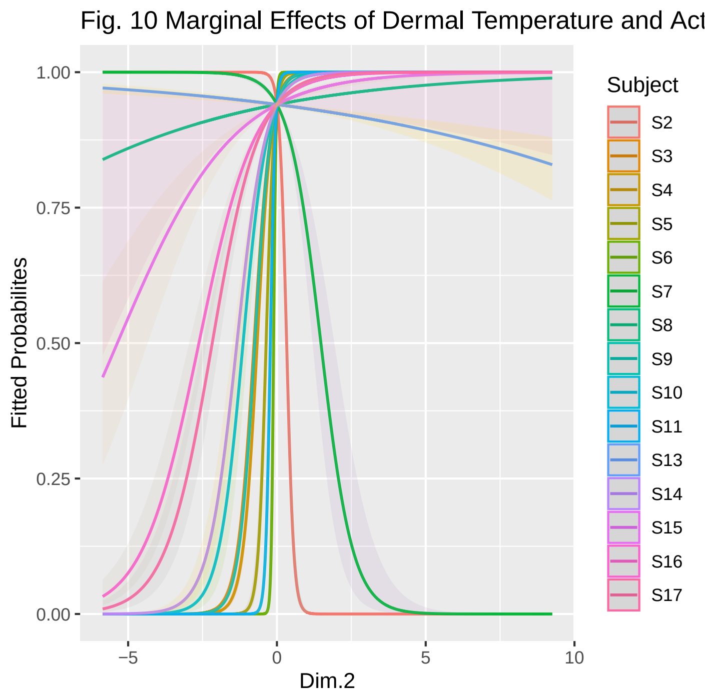
```
## Scale for 'y' is already present. Adding another scale for 'y', which will
## replace the existing scale.
```

```
## Warning in RColorBrewer::brewer.pal(n, pal): n too large, allowed maximum for palette Set1 is 9
## Returning the palette you asked for with that many colors
```

```
## Scale for 'colour' is already present. Adding another scale for 'colour',
## which will replace the existing scale.
```

```
## Scale for 'y' is already present. Adding another scale for 'y', which will
## replace the existing scale.
```






```
## Warning in RColorBrewer::brewer.pal(n, pal): n too large, allowed maximum for palette Set1 is 9
## Returning the palette you asked for with that many colors

## Scale for 'colour' is already present. Adding another scale for 'colour',
## which will replace the existing scale.

## Scale for 'y' is already present. Adding another scale for 'y', which will
## replace the existing scale.

## Warning in RColorBrewer::brewer.pal(n, pal): n too large, allowed maximum for palette Set1 is 9
## Returning the palette you asked for with that many colors

## Scale for 'colour' is already present. Adding another scale for 'colour',
## which will replace the existing scale.
## Scale for 'y' is already present. Adding another scale for 'y', which will
## replace the existing scale.
```

Fig. 11 Marginal Effects of Heart Rate

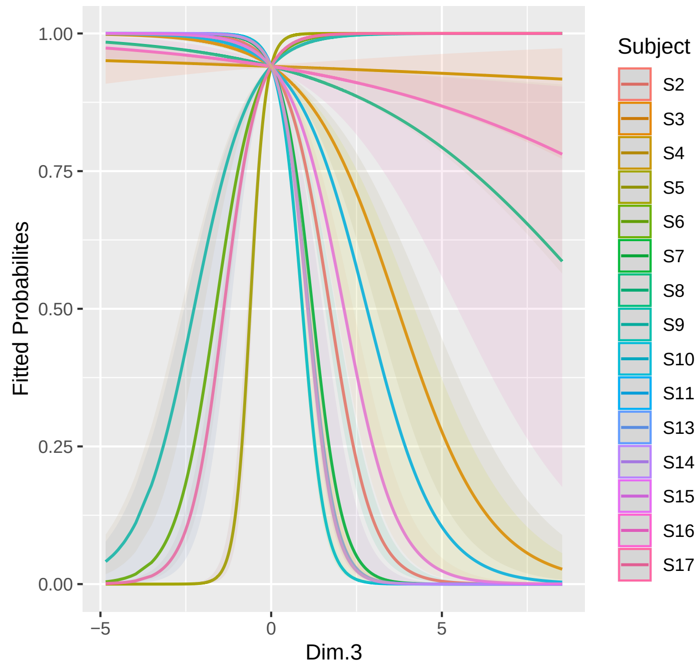
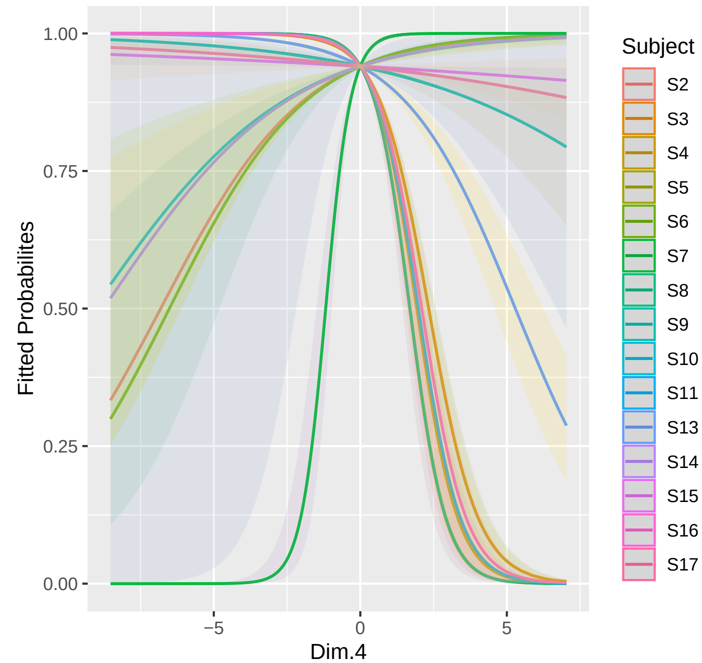


Fig. 12 Marginal Effects of Neuro−Muscular Activity



We used to combined data model to understand the relationship between the various physioloigcal components and stress. From Table ___, we see that increases in the variability in movement and dermal temperature and activity are associated with a multiplicative increase in the odds of stress. Conversely, increases in the variability of heart rate and neuro-muscular activity is associated with a multiplicative decrease in the odds that the state is stress. However, in order to determine if these trends are homogeneous, we added interaction effects between subjects and the principal components to the combined data model.

Figures **, , , and** show the fitted probability of stress against each principal component, with different colors representing different subjects. From figure ___ , we see that as the variation in motion 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 ___ shows that as the variation in mean dermal temperature and activity 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 ___ shows that heart rate 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. Though the remaining subjects exhibit a seemingly “unnatural” trend, with the probability of stress *decreasing* with an increased heart rate, research has found that anxiety can be linked to a slowing heart rate as well [19].

Figure ___ shows that as neurological and muscular activity increase, the probability of stress decrease similarly for all subjects barring subjects 2, 6, 7, 10, and 14. For these five subjects, the probabilities increase. For these individuals, as neuro-muscular activity increases, the odds of stress increases as well.

These behaviors can be corroborated by the coefficient estimates in A.6. When adding together the main effect of a principal component and its interaction with a particular subejct, it can be noted that a positive values corespond with an increasing trend in the above plots. Conversely, a negative value will correspond with a decreaseing trend. This is consistent with the notion that positive coefficients in logsitic regression indicate a multiplicative increase in odds, while negative coefficients indicate a decrease.

Table _____ show 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 2. The ROC curve in figure ___ shows that our final model discriminates moderately well between the stress and amusement states. Specifically, the area under the curve is 0.8874232.

4.1 Conclusions and Limitations

In conclusion, sensor data is useful in discriminating between stress and amusement conditions. While only using wrist 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 more variability in movement and dermal conditions is related to a greater likelihood of stress, whereas more variability in heart rate and neuro-muscular measures is related to a lesser likelihood of stress. Adding interaction effects between the 15 subjects and the physiological components showed differences among the subjects' physiological states when stressed. For instance, some subjects had higher average heart rate while stress while others exhibited the opposite.

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 ____. 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, 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, population-wide understanding of heterogeneity in stress response.

5 References

1. https://www.nimh.nih.gov/health/publications/stress/index.shtml?fbclid=IwAR0dCMkPveUAxNd_JNih1SQ3-a8wGBJ66Z9EkhVZ4lBH_Ayw4jzTSeN4M3Y#:~:text=Over%20time%2C%20continued%20strain%20

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3. https://www.mayoclinic.org/tests-procedures/ekg/about/pac-20384983

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5. https://link.springer.com/referenceworkentry/10.1007%2F978-1-4419-1005-9_13#:~:text=Electrodermal%20activ

6. https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4664114/#:~:text=Acute%20stress%20triggers%20peripheral%2

7. https://ieeexplore.ieee.org/document/7949491

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11. https://github.com/DigitalBiomarkerDiscoveryPipeline/Human-Activity-Recognition/blob/master/10_code/30_end_pre_processing/32_engineer_features/33_feature_engineering.ipynb

12. (https://statisticsbyjim.com/regression/multicollinearity-in-regression-analysis/#:~:text=Multicollinearity%20rec

13. (https://medicalxpress.com/news/2018-07-heart-affects.html).

14. (http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.705.8139&rep=rep1&type=pdf)

15. (https://support.minitab.com/en-us/minitab/19/help-and-how-to/quality-and-process-improvement/control-charts/supporting-topics/understanding-attributes-control-charts/overdispersion-and-underdispersion/#:~:text=Underdispersion%20exists%20when%20data%20exhibit,other%2C%20also%20known%20as%20autocorre

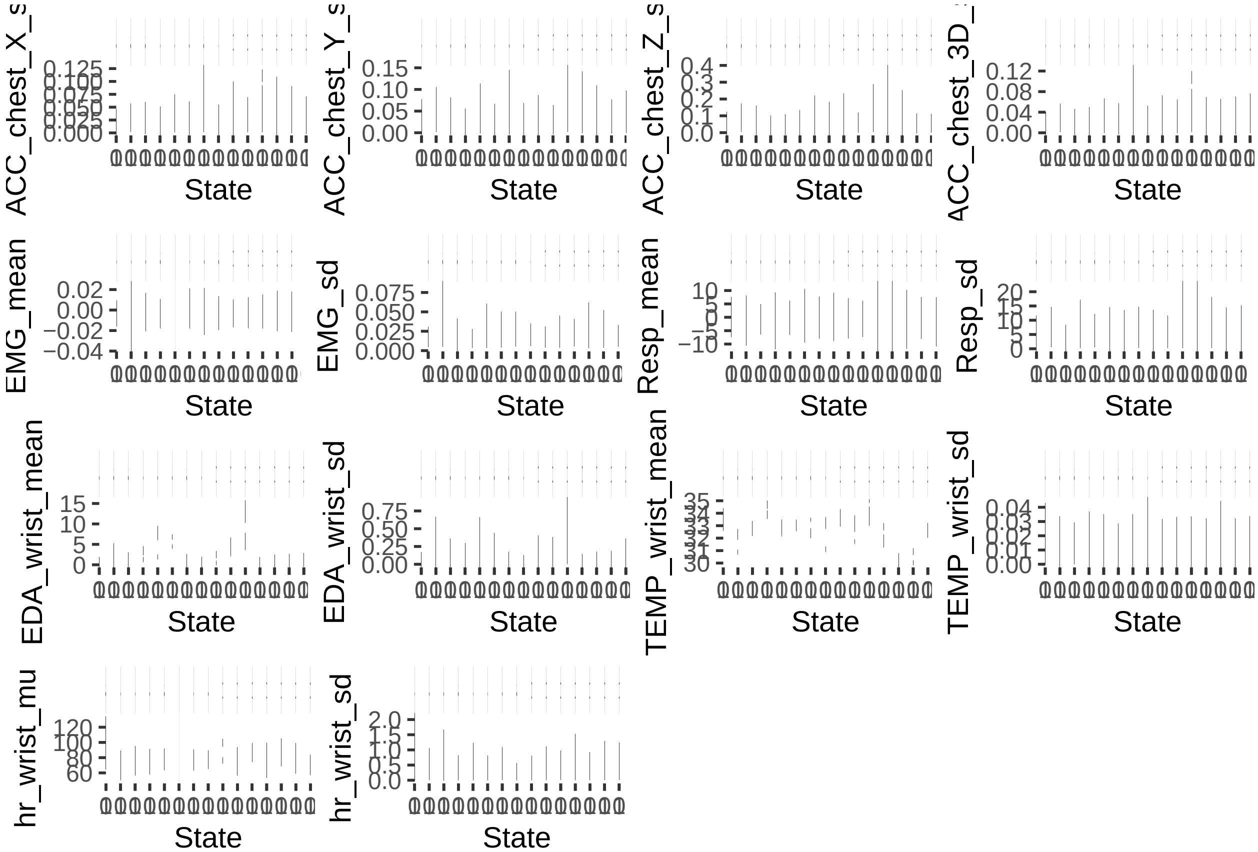
16. (https://www.theanalysisfactor.com/tips-principal-component-analysis/#:~:text=2.,have%20similar%20scales%20

17.

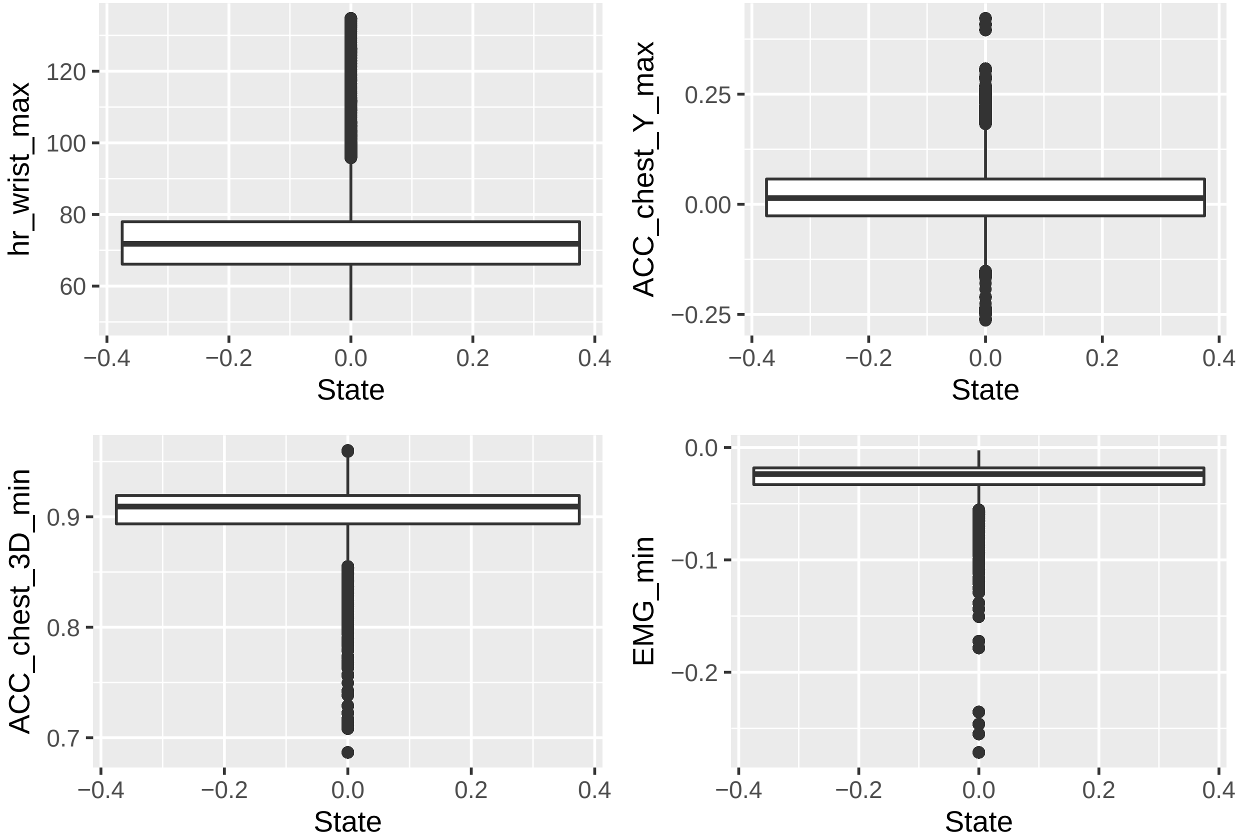
6 Appendix

6.1 A.1

```
varvslab<- function(var) {
  ggplot(remove_select_cov, aes_(y=as.name(var), x=factor(remove_select_cov$Label), group = factor(r
    labs(x ="State", y = as.name(var))
}
do.call(grid.arrange, lapply(names(remove_select_cov_nb), varvslab))
```

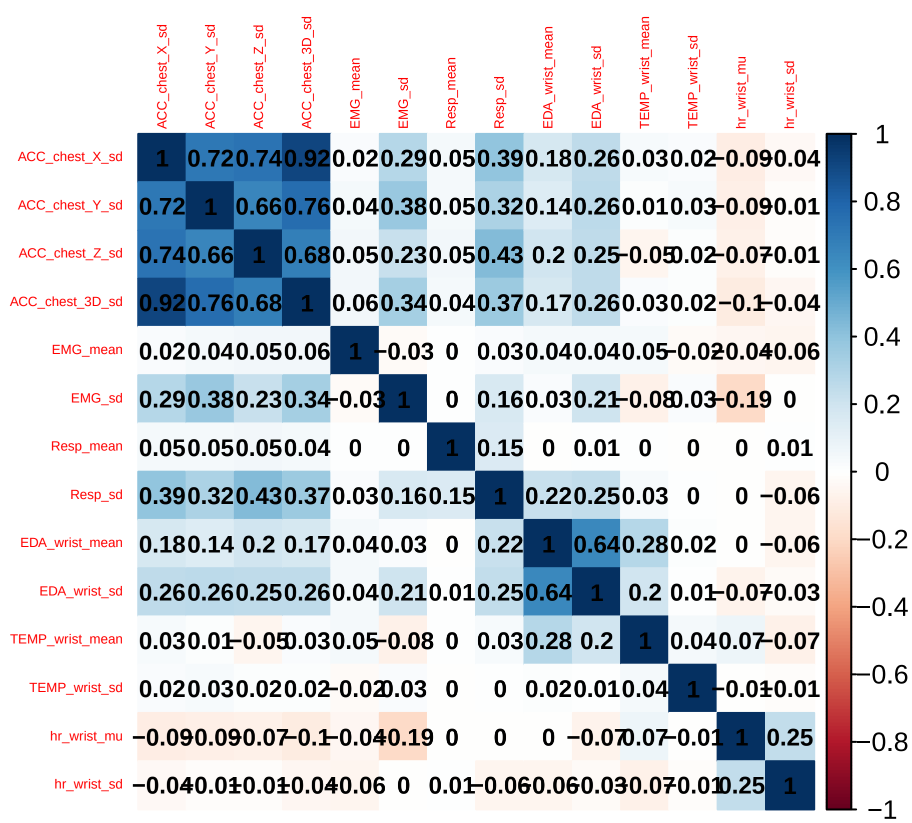


6.2 A.2

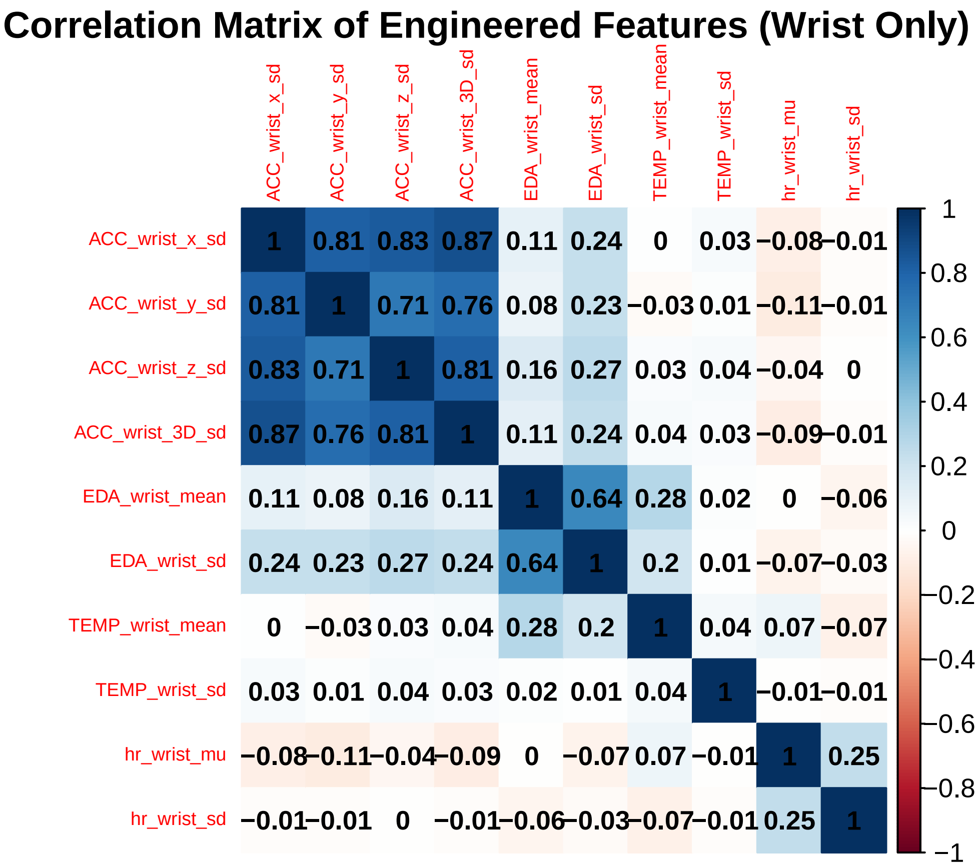


6.3 A.3

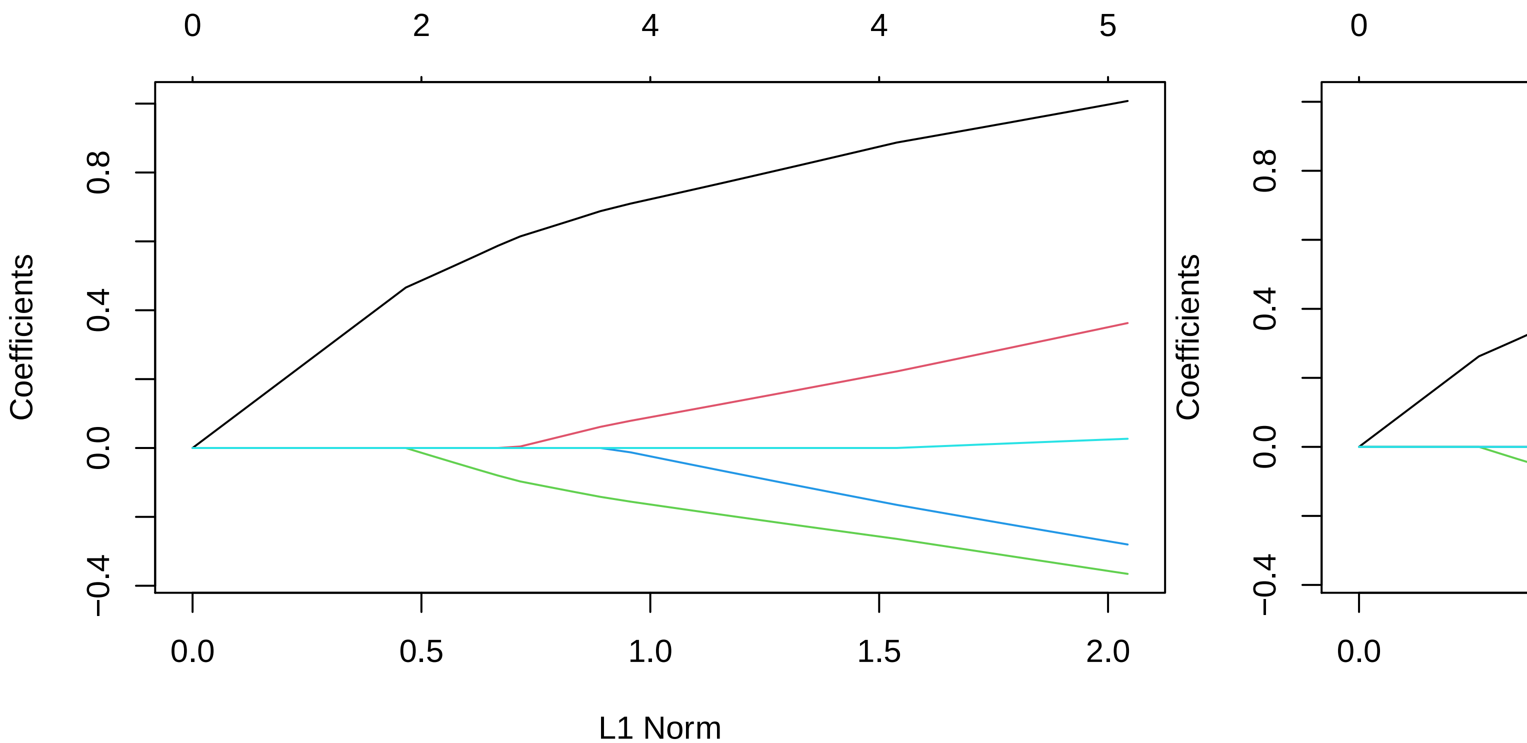
Correlation Matrix of Engineered Features



```r
cormatrix = cor(wrist_nb)
corrplot::corrplot(cormatrix, method = "color", addCoef.col="black", tl.cex = 0.6, number.cex= 8/ncc
```

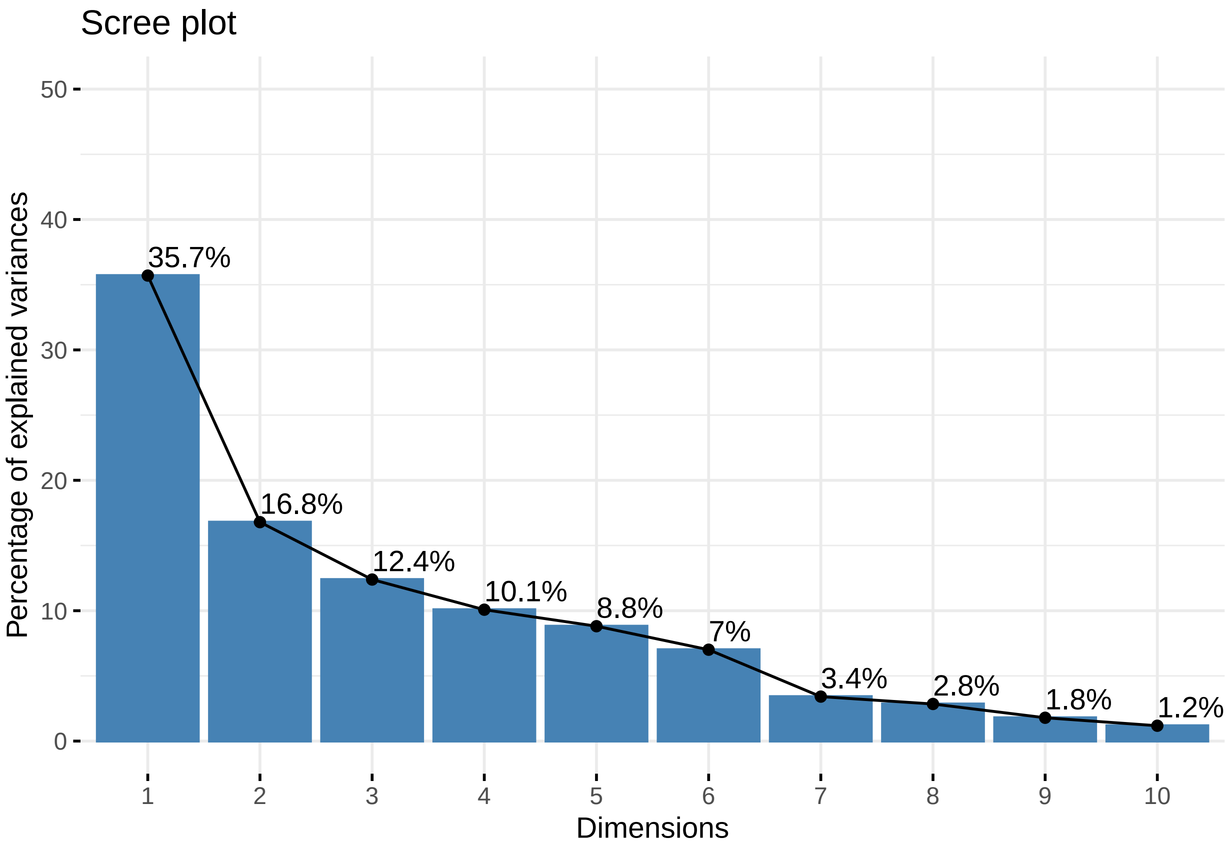


6.4 A.4

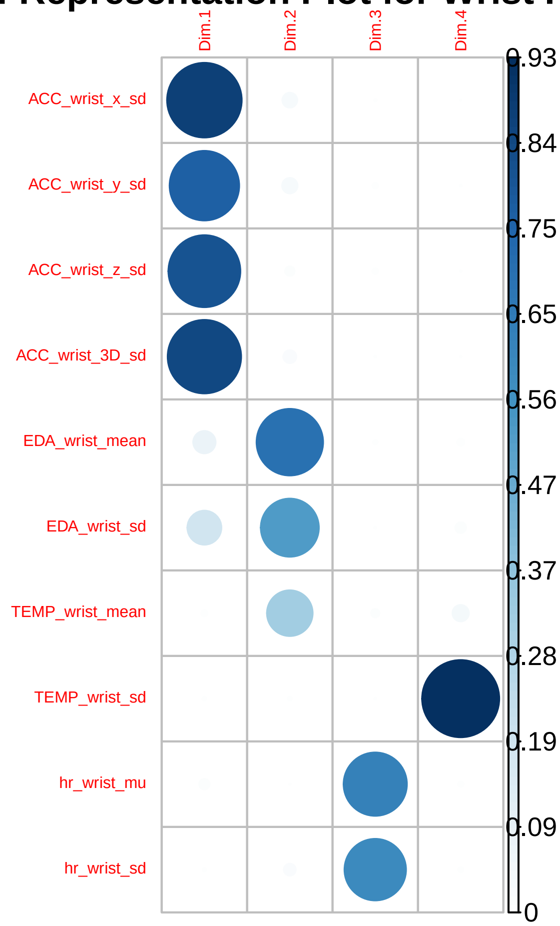


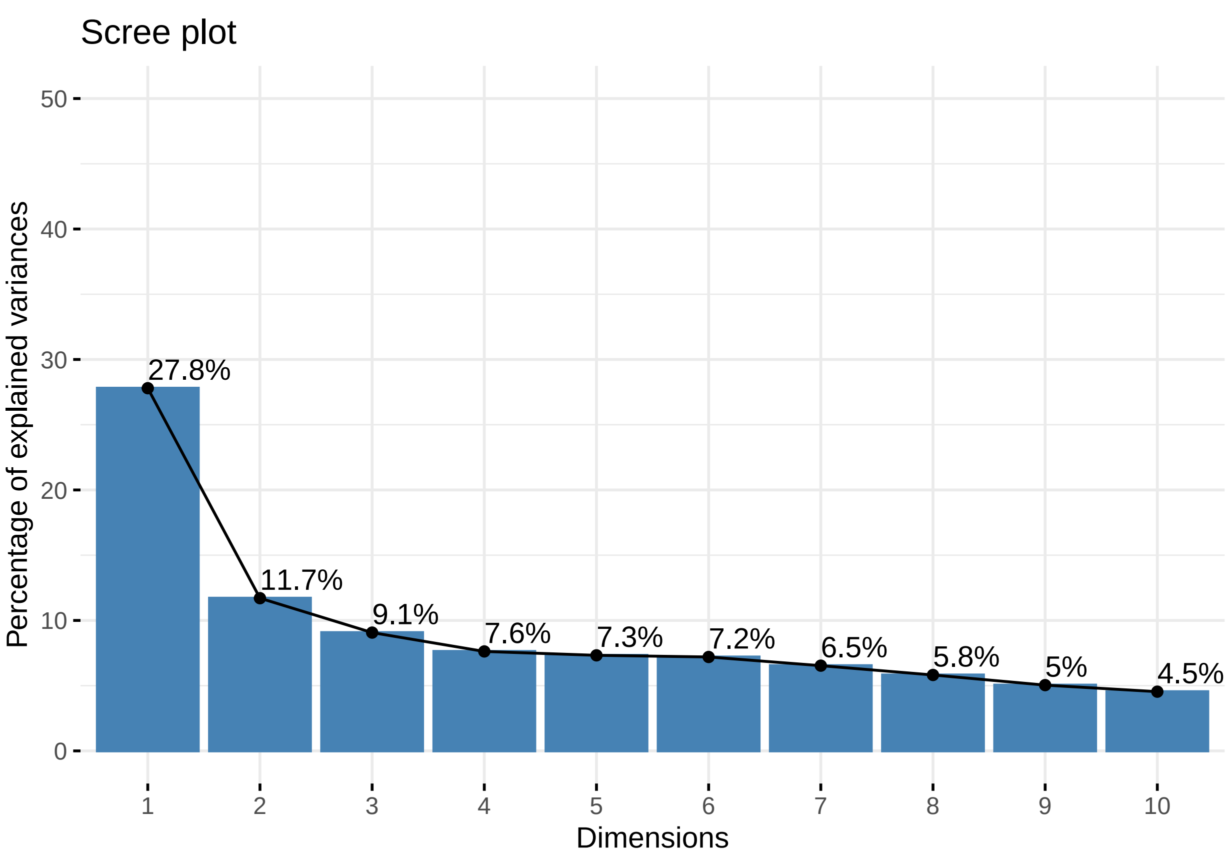
6.5 A.5

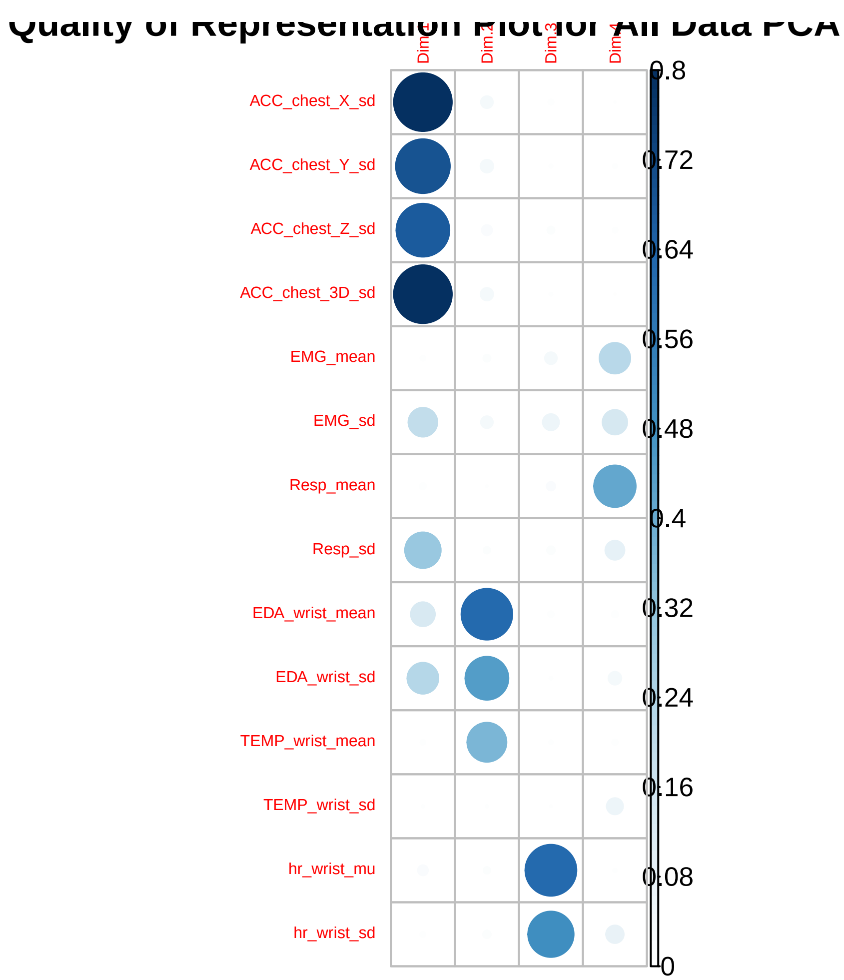
```r
scaled_wrist_nb = scale(wrist_nb, center = TRUE, scale = TRUE)
res.pca <- PCA(scaled_wrist_nb, graph = FALSE, ncp = 4)
eig.val <- get_eigenvalue(res.pca)
#eig.val
fviz_eig(res.pca, addlabels = TRUE, ylim = c(0, 50))
```



Quality of Representation Plot for Wrist PCA







6.6 A.6

```
##
## 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 ***
## Dim.2:SubjectS6  33.04259    1.70286  19.404  < 2e-16 ***
## Dim.2:SubjectS7   6.56933    0.46842  14.025  < 2e-16 ***
## Dim.2:SubjectS8   8.62471    0.43988  19.607  < 2e-16 ***
## Dim.2:SubjectS9  12.13523    0.42372  28.640  < 2e-16 ***
## Dim.2:SubjectS10 10.85709    0.45676  23.770  < 2e-16 ***
## Dim.2:SubjectS11 20.90306    0.69993  29.865  < 2e-16 ***
## Dim.2:SubjectS13  8.30807    0.41217  20.157  < 2e-16 ***
## Dim.2:SubjectS14 10.48645    0.42848  24.473  < 2e-16 ***
## Dim.2:SubjectS15  8.94947    0.41727  21.448  < 2e-16 ***
## Dim.2:SubjectS16  9.48707    0.41735  22.732  < 2e-16 ***
## Dim.2:SubjectS17  9.70360    0.42230  22.978  < 2e-16 ***
## 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 ***
## Dim.3:SubjectS10 -1.41101    0.10794 -13.072  < 2e-16 ***
## 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
```