College of Engineering
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AMD: Analysis of Mood Dysregulation

A Machine Learning Approach

Master's Thesis Defense

By:
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Components

- Introduction
- Related Work
- mAAS System Improvements
- Mood Study Overview
- AMD Pipeline
- Results and Model Comparison
- Knowledge Gained and Future Work

Components

- Introduction
  - Problem
  - Solution
  - Contributions
  - AMD Overview
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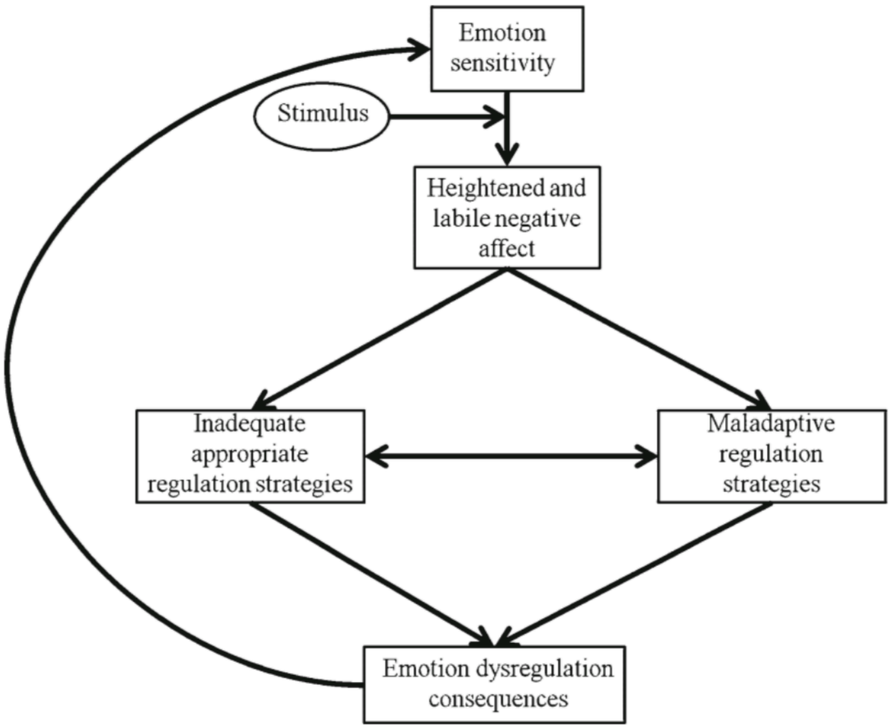
Introduction

- Mood dysregulation is the inability to flexibly respond to and manage emotions
  - Theorized to be sensitive to emotion from birth
- As a result, mood dysregulation consequences occurs
  - Such as stress or other emotion sensitivity



Carpenter, R.W. & Trull, T.J. Curr Psychiatry Rep (2013) 15: 335. doi:10.1007/s11920-012-0335-2

Introduction

- If you are alive, then you have mood variability
  - Stress kills, can lead to or worsen heart diseases and cancer
- Human studies show mood dysregulation causes psychological and behavioral problems
  - Such as stress, depression, addiction, rage, anxiety and other mood dysregulation issues
- How can we analyze and study mood dysregulation ?

Problem

1. Most methods in clinical psychology research primarily rely on questionnaires and interviews
   – With examiners in lab setting
2. Humans have a hard time understanding mood dysregulation using these methods
   – To much data to analyze by hand
   – Difficult to see trends in the data

Solution

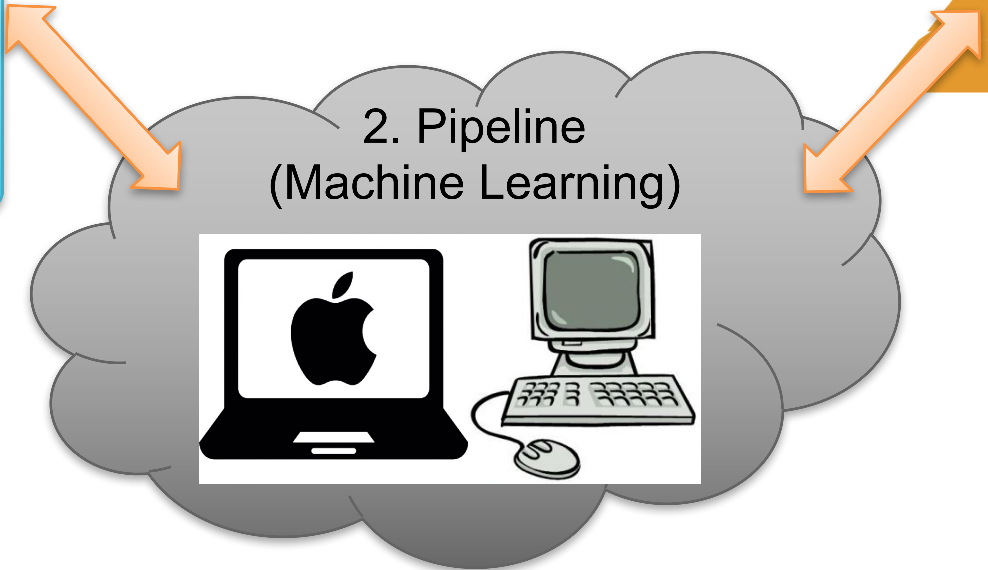
1. Mobile ambulatory assessment in natural real-world environments
   - Using smartphones and physiological wearable body metrics
2. Machine learning models can be developed to identify changes in mood, stress, as well as other psychological problems
   - Possible by combining information about:
     - External environment, participants' physiological and mental states
   - Collected through random system-generated and user-initiated self-reports surveys

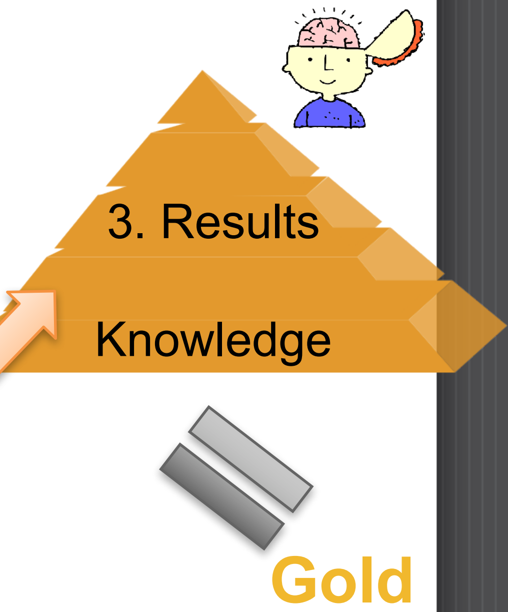
Contributions

- 1. mAAS System Improvements
  - Hardware and user information during study
  - Upload missing data from mobile device
  - Obtaining and displaying data from Hexoskin
- 2. AMD Pipeline
  - Data combination and organization, data selection and removal, data smoothing, feature extraction and creation
  - Classification of Mood Dysregulation in the Natural Environment
    - Based on multiple machine learning models
    - Achieve over 90% accuracy when including time attributes

AMD Workflow Overview

“Logic is not the end of wisdom, it is just the beginning” -- Spock





Components

- Introduction
- Related Work
  - Continuous inference, *2011*.
  - Recognizing mental stress, 2013.
  - Profiling visual and verbal stress responses, 2013.
  - Finding Significant Stress Episodes, 2016.
- mAAS System Improvements
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Related Work

1. Plarre, K., Raij, A., Hossain, S. M., Ali, A. A., Nakajima, M., Al'absi, M., ... & Siewiorek, D. (2011, April). Continuous inference of psychological stress from sensory measurements collected in the natural environment. In *Information Processing in Sensor Networks (IPSN), 2011 10th International Conference on* (pp. 97-108). IEEE.
   - Similar project except they are studying stress
   - Helped me with the data cleaning process and feature selection
   - Received approximately 90% accuracy when removing around 70% of the data due to physical activity, poor quality or losses in transmission, etc.

Related Work (cont.)

2. Eggert, C., Lara, O. D., & Labrador, M. A. (2013, April). Recognizing mental stress in chess players using vital sign data. In *Southeastcon, 2013 Proceedings of IEEE* (pp. 1-4). IEEE.
    - Developed system to recognize psychological stress without human subjective bias
    - Use physiological sensors during chess match
    - Determine which moves caused the player to become stressed during the chess match

Related Work (cont.)

3. Bouarfa, L., Bembnowicz, P., Crewther, B., Jarchi, D., & Yang, G. Z. (2013, May). Profiling visual and verbal stress responses using electrodermal heart rate and hormonal measures. In *2013 IEEE International Conference on Body Sensor Networks* (pp. 1-7). IEEE.
   - Discriminate stress responses from watching videos and speaking using Electro-dermal activity and heart rate variability measures
   - Using 17 features calculated from signals
   - 4 Classifiers were investigated with maximum accuracy of 92% achieved for differentiating stress responses

Related Work (cont.)

4. Sarker, H., Tyburski, M., Rahman, M. M., Hovsepian, K., Sharmin, M., Epstein, D. H., ... & al'Absi, M. (2016, May). Finding Significant Stress Episodes in a Discontinuous Time Series of Rapidly Varying Mobile Sensor Data. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (pp. 4489-4501). ACM.

   – Delivering sensor-triggered just-in-time interventions (JITIs) on mobile devices for the management of daily stress

   – 38 users with 4 weeks of physiological, GPS, and activity data

   – Found that the duration of a prior stress episode predicts the duration of the next stress episode

Components

- Introduction
- Related Work
- Mobile Ambulatory Assessment System (mAAS) Improvements
  - mAAS Overview and Introduction
  - mAAS Hardware Information Collection
  - Uploading Missing Survey Data from Mobile Devices
  - Obtaining and Displaying Sensor Data from Hexoskin
- Mood Study Overview
- AMD Pipeline
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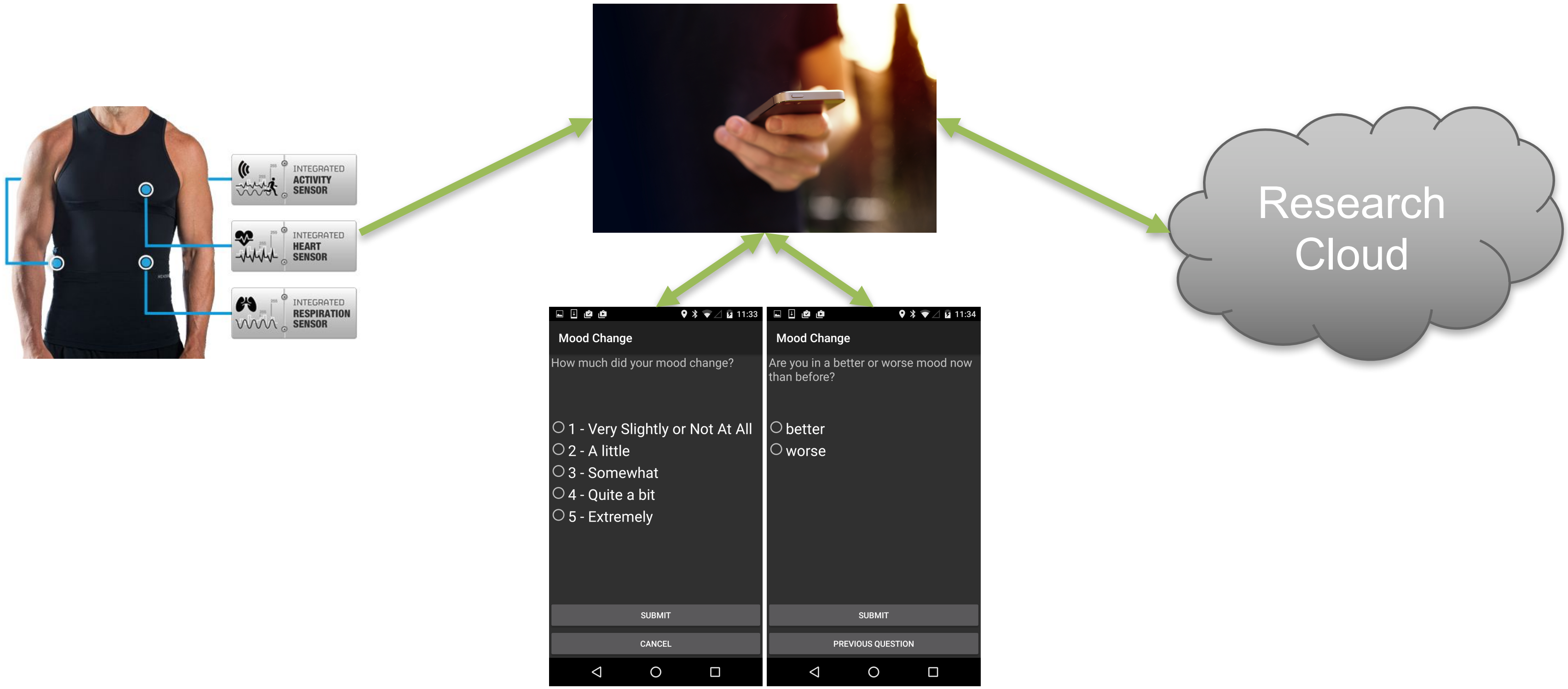
mAAS Overview

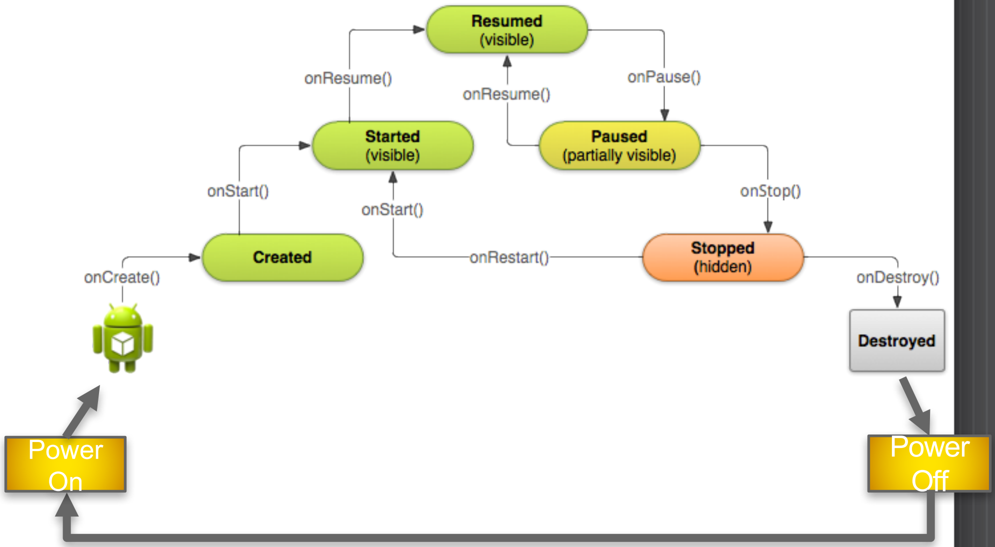


mAAS System Problems

1. Unknown application errors
   – Generated by user or mobile device application
2. Missing survey data
   – Caused when application was not connected to Internet
3. Obtaining physiological data from Hexoskin
   – Could only go through dashboard downloading one file at a time

mAAS Hardware Information Collection

- Monitoring system for hardware on mobile phone
  - Can determine if user turns on/off phone, starts/stops application, Internet connectivity, and many more
  - Used when we did not know if the user was causing error or the application itself
    - Some users claim app not working when in reality, they were not connected to internet, or had the phone off



Example Output

- Every 5 Minutes:
  - Data collected here was sent to the server on 5 minute intervals
  - Effected the battery use minimally

```
Tue Sep 29 04:50:39 CDT 2015

Is Phone Charging? -> true
  Charging By: AC Outlet
Battery Level: 1.0
Network Connection Status: Connected
  MOBILE: CONNECTED
  WIFI: UNKNOWN
  BLUETOOTH for Network: UNKNOWN
  Is Phone Connected To Active Network? -> true
GPS Mode in Phone Settings: LOCATION_MODE_SENSORS_ONLY
  Is There an Active GPS Signal? -> true
  Longitude and Latitude: 38.88794724, -92.34900453
  GPS Provider: gps
  GPS Accuracy: 17.0 meters
  Is the GPS Accuracy Good? -> true
  Will this GPS location be recorded? -> true
Is BLUETOOTH for Device Supported? -> true
  Is BLUETOOTH for Device On? -> false
Airplane Mode Is On: false
---------------------------------------
```

Example Output

- Asynchronous:

```
----------------------------------------
Fri May 29 09:54:26 CDT 2015
Device was TURNED ON by user! And just finished starting up.
----------------------------------------
Fri May 29 09:54:28 CDT 2015
Bluetooth is TURNING ON and was activated by the user !!
----------------------------------------
Fri May 29 09:54:29 CDT 2015
Bluetooth's Current State: ON
----------------------------------------
```

```
Tue May 26 17:55:11 CDT 2015
User has just STARTED the app!
---------------------------------------
```

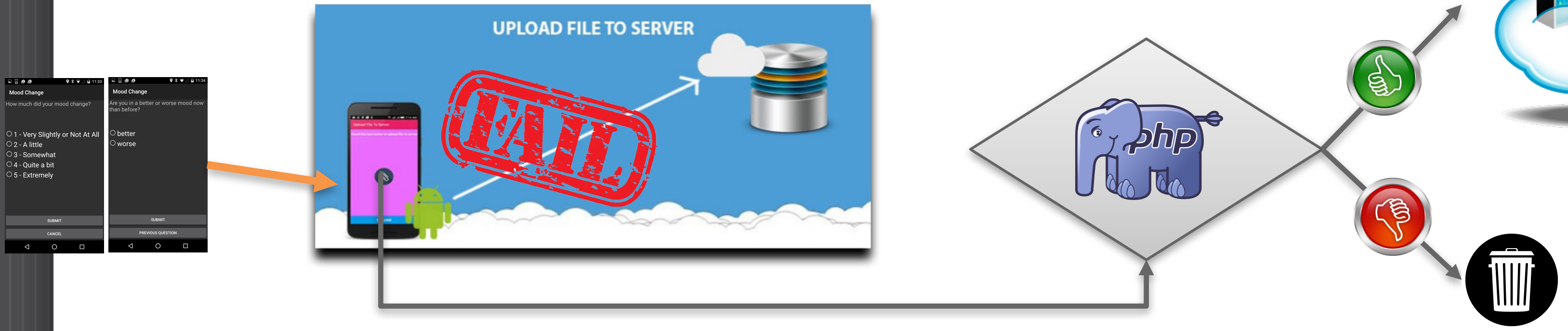
```
Sun Apr 12 16:49:15 CDT 2015
Bluetooth Pairing State is CONNECTING to the Device Named 'Nickolas's MacBook Pro' !!
---------------------------------------
Sun Apr 12 16:49:18 CDT 2015
Active Bluetooth has just been CONNECTED to the Device Named 'Nickolas's MacBook Pro' !!
---------------------------------------
```

```
            User: 0101, Thu Mar 03 17:47:07 CST 2016

The System Clock was JUST CHANGED by user!

The previous time was: Thu Mar 03 19:58:08 CST 2016
The new time is: Thu Mar 03 17:47:07 CST 2016
---------------------------------------
```

```
---------------------------------------
Tue May 26 18:18:22 CDT 2015
User has just CLOSED the app!
---------------------------------------
```

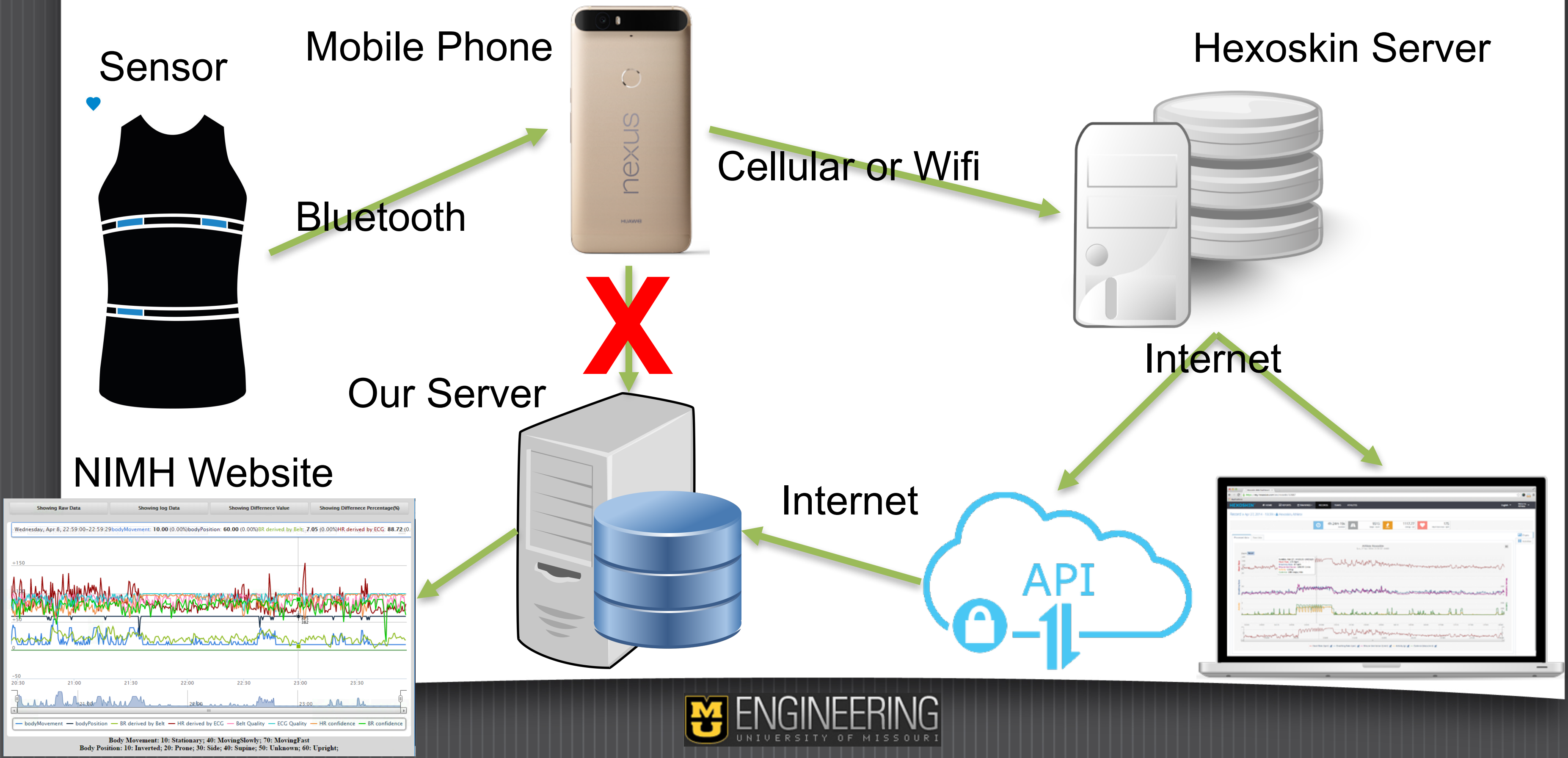
```
----------------------------------------
Fri May 29 14:54:46 CDT 2015
Device is TURNING OFF! And was activated by user!
----------------------------------------
Fri May 29 14:54:47 CDT 2015
Bluetooth is TURNING OFF and was activated by the user !!
----------------------------------------
Fri May 29 14:54:54 CDT 2015
Bluetooth's Current State: OFF
----------------------------------------
```

Upload Missing Survey Data



- <u>Problem:</u> If data does not make it to server, app will not re-upload data and data will remain on phone
  - Psychology department would have to pull data off phone manually
- <u>Solution:</u> An easy to use function on phone, activated by button, to upload all data on phone
  - Server program to handle duplicates and other situations

Obtain Hexoskin Data Workflow



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- Mood Study Overview
  - Mood Study Procedure
  - Statistics Analysis
  - Visual Statistics
  - Machine Learning (ML) Overview in Study
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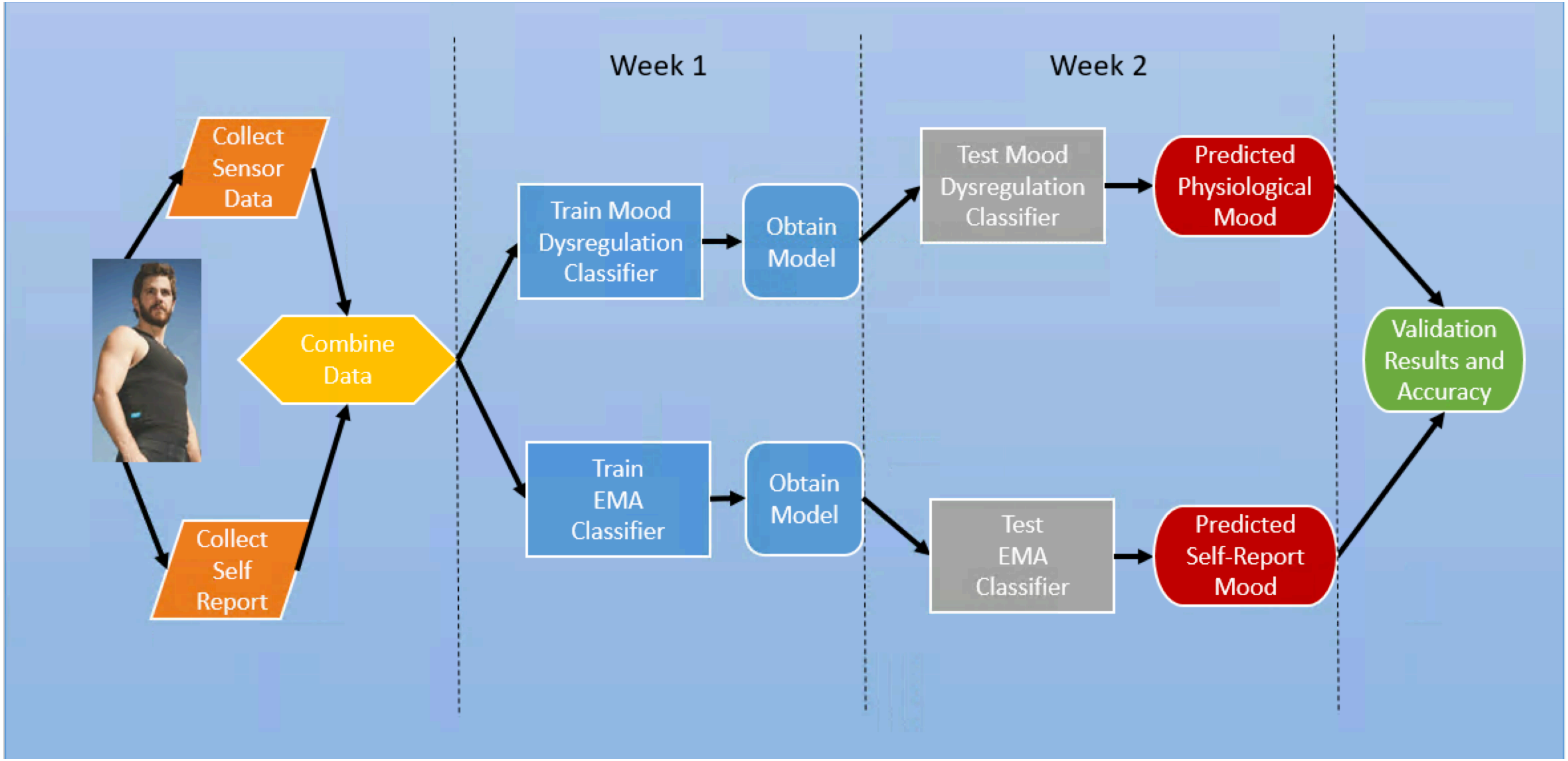
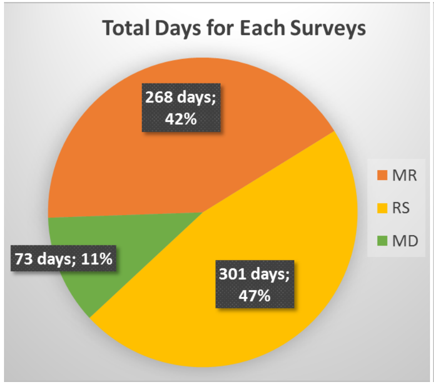
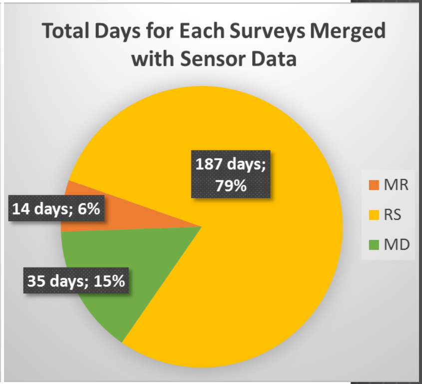
Mood Study Procedure

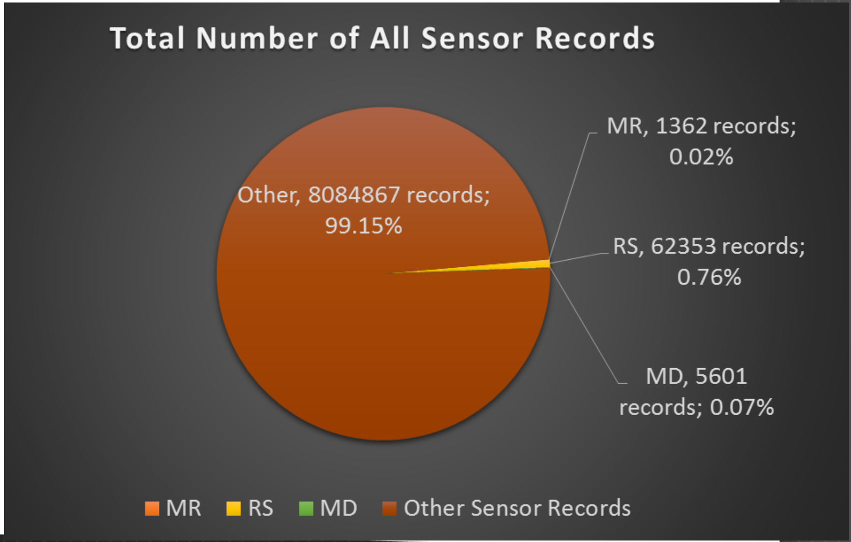


Statistical Analysis

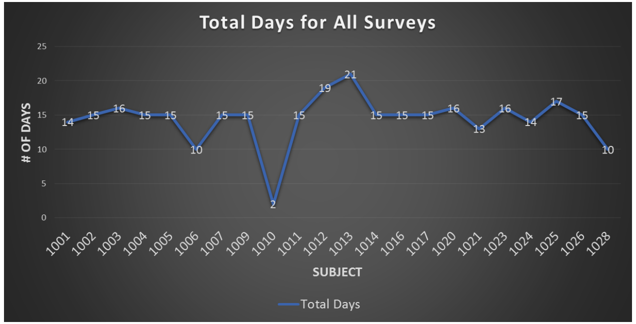
- Hexoskin Sensor Attributes
  - Heart and breathing rate, activity, RR interval, minute ventilation, tidal volume, inspiration and expiration, cadence
- 22 subjects in natural environment
- 318 days of surveys
- 258 days of sensor data
- 8,154,183 sensor records
- After combining with survey data
  - 69,316 associated survey and sensor records
  - -99.15% decrease
  - Less than 1% of sensor data corresponds to survey data

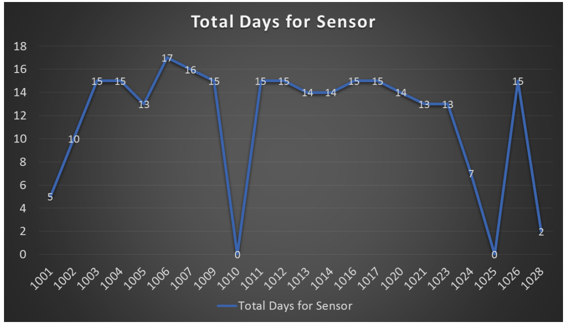


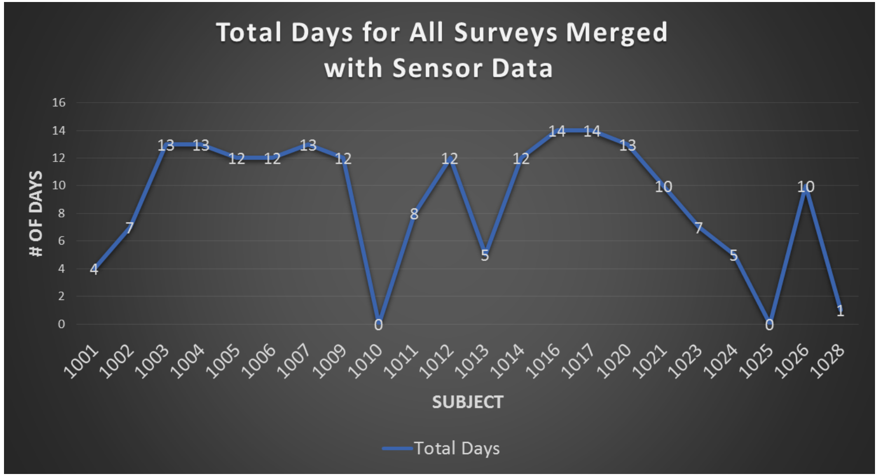


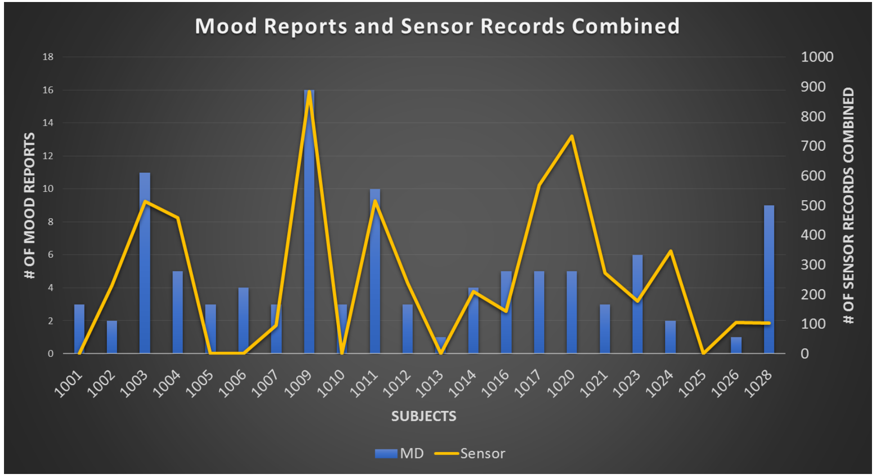


Visual Statistics Physiological

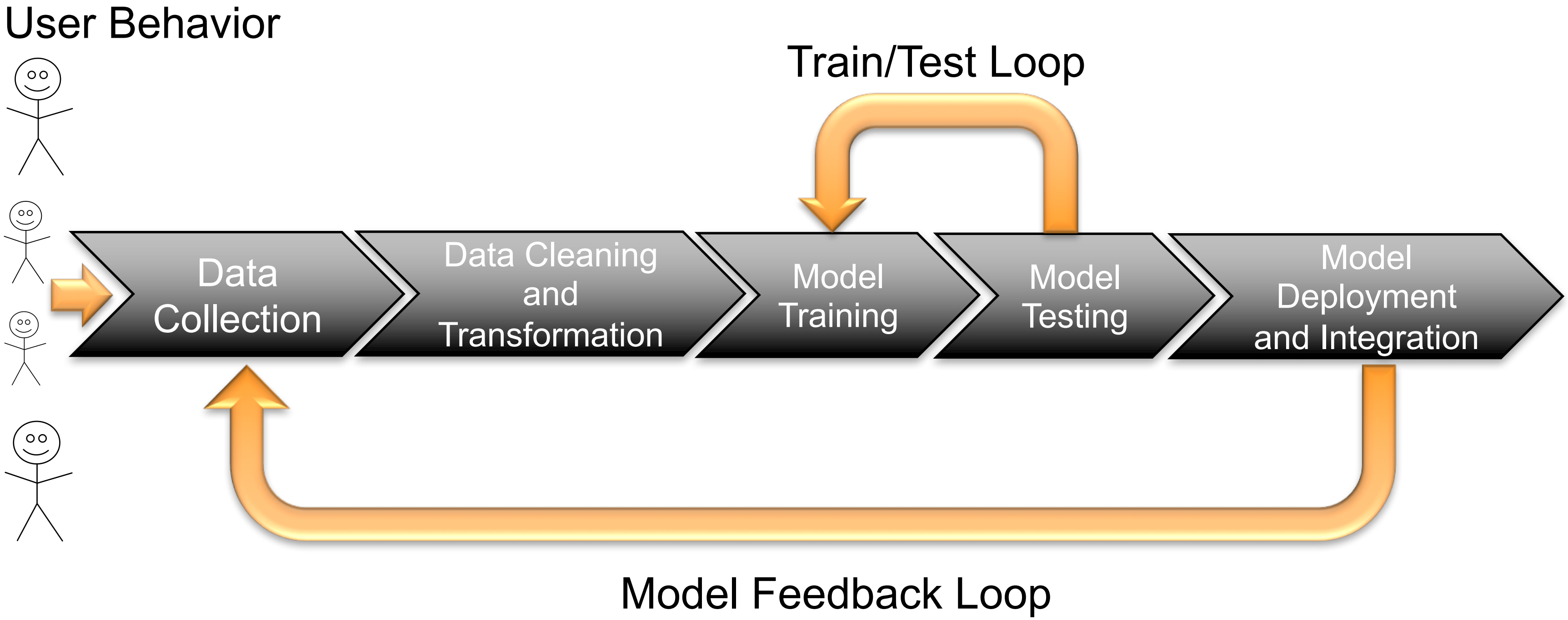








ML Incorporated in Study



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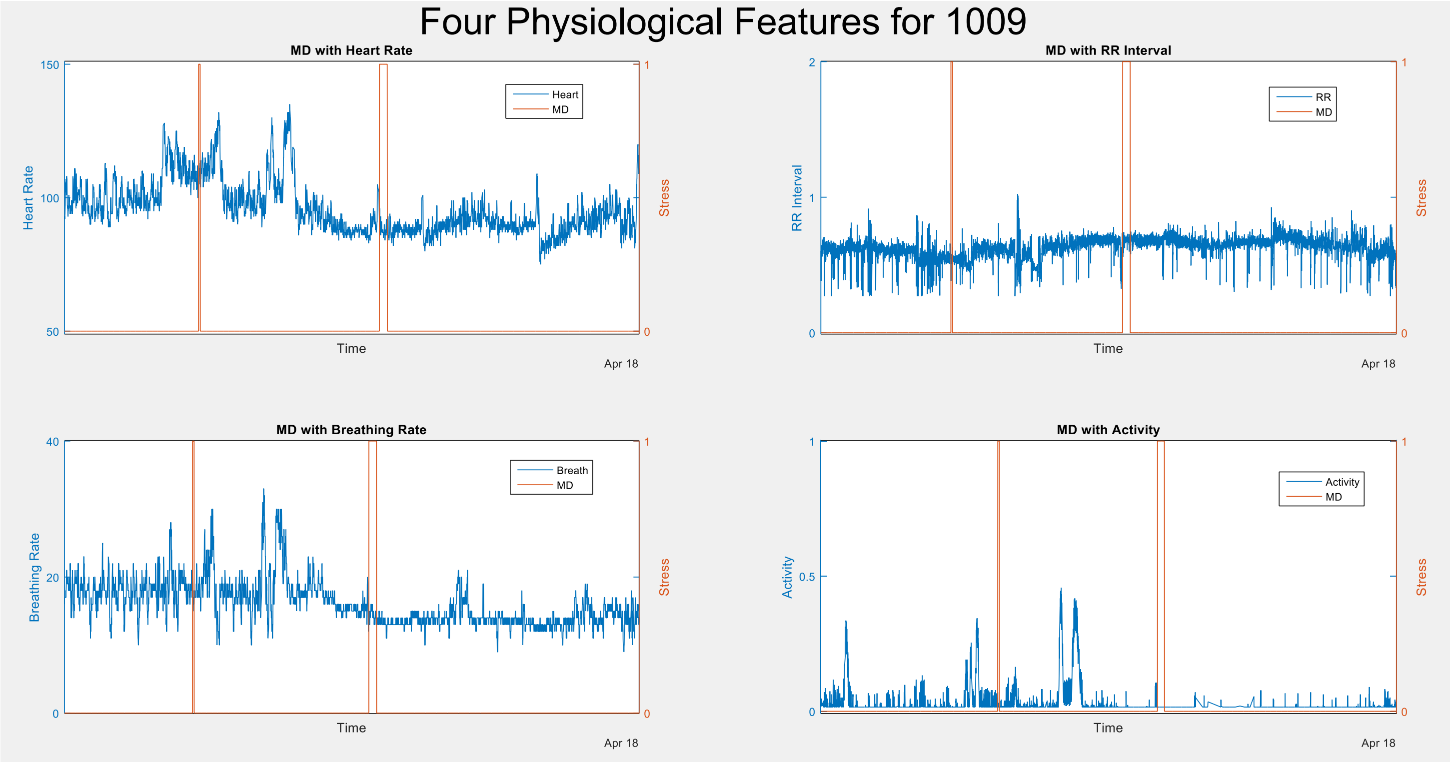
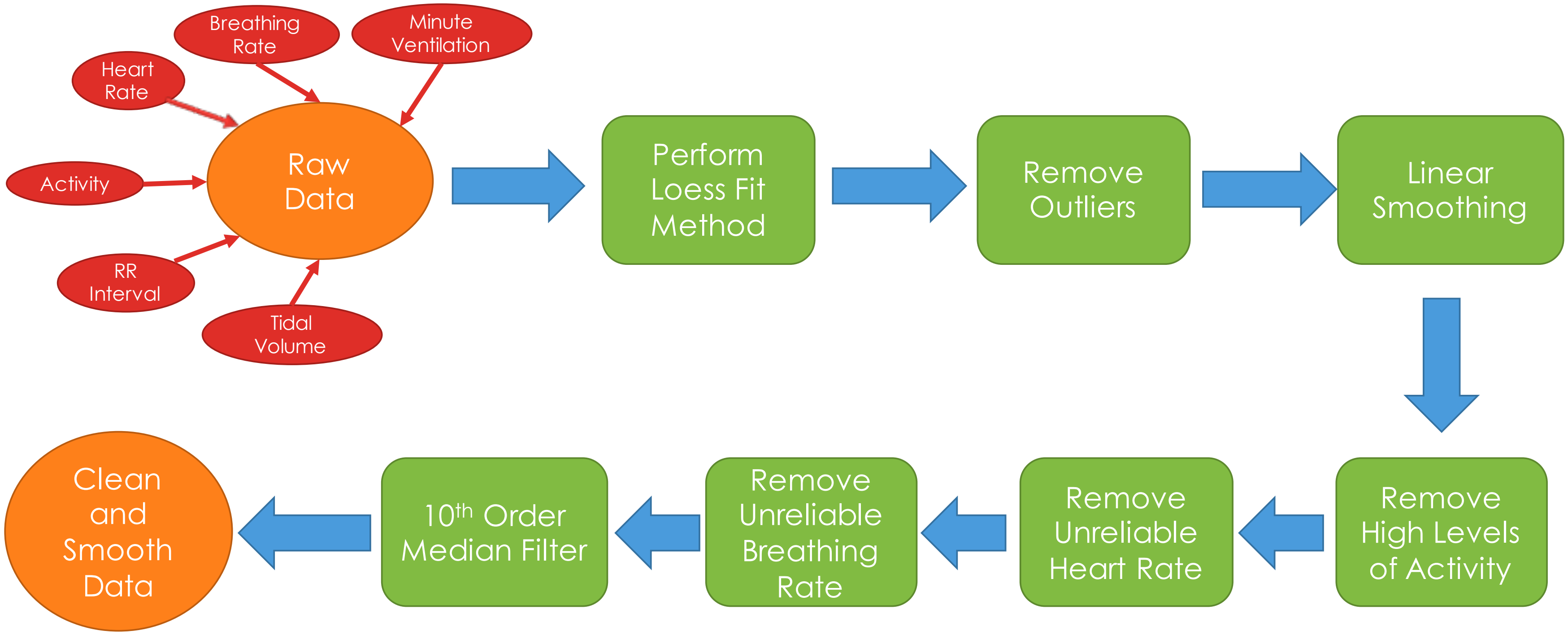
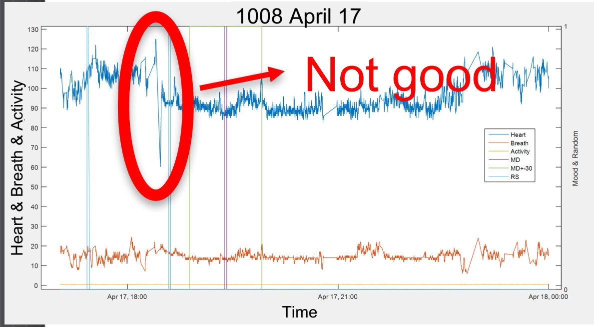
Hexoskin Data

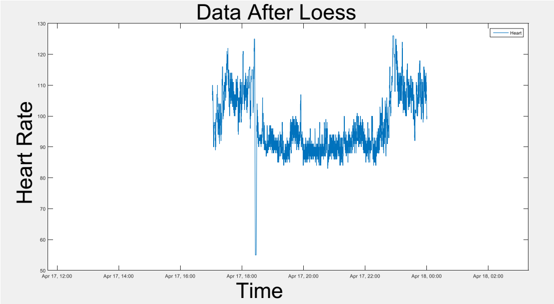


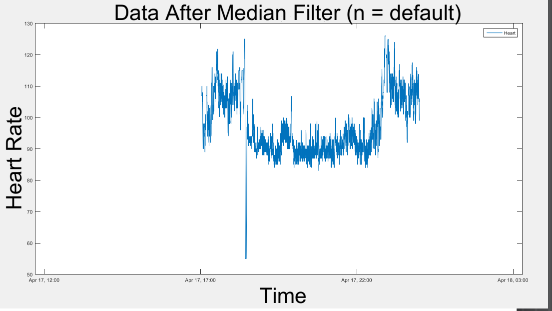
Naïve Cleaning Pipeline

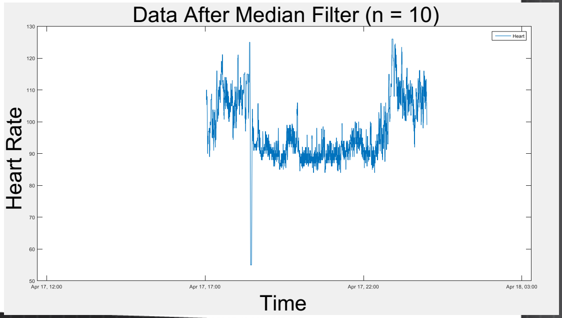


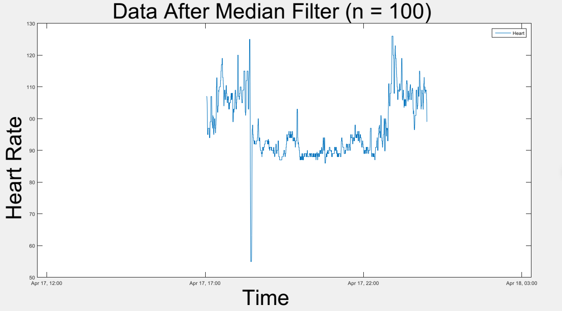
Naïve Cleaning Pipeline

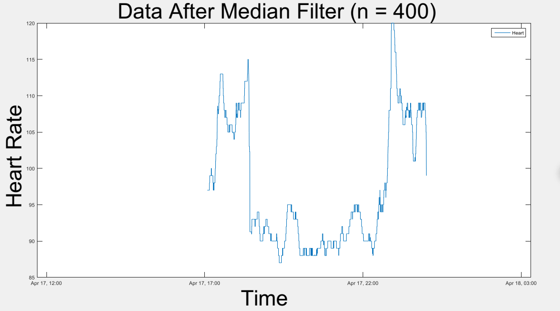




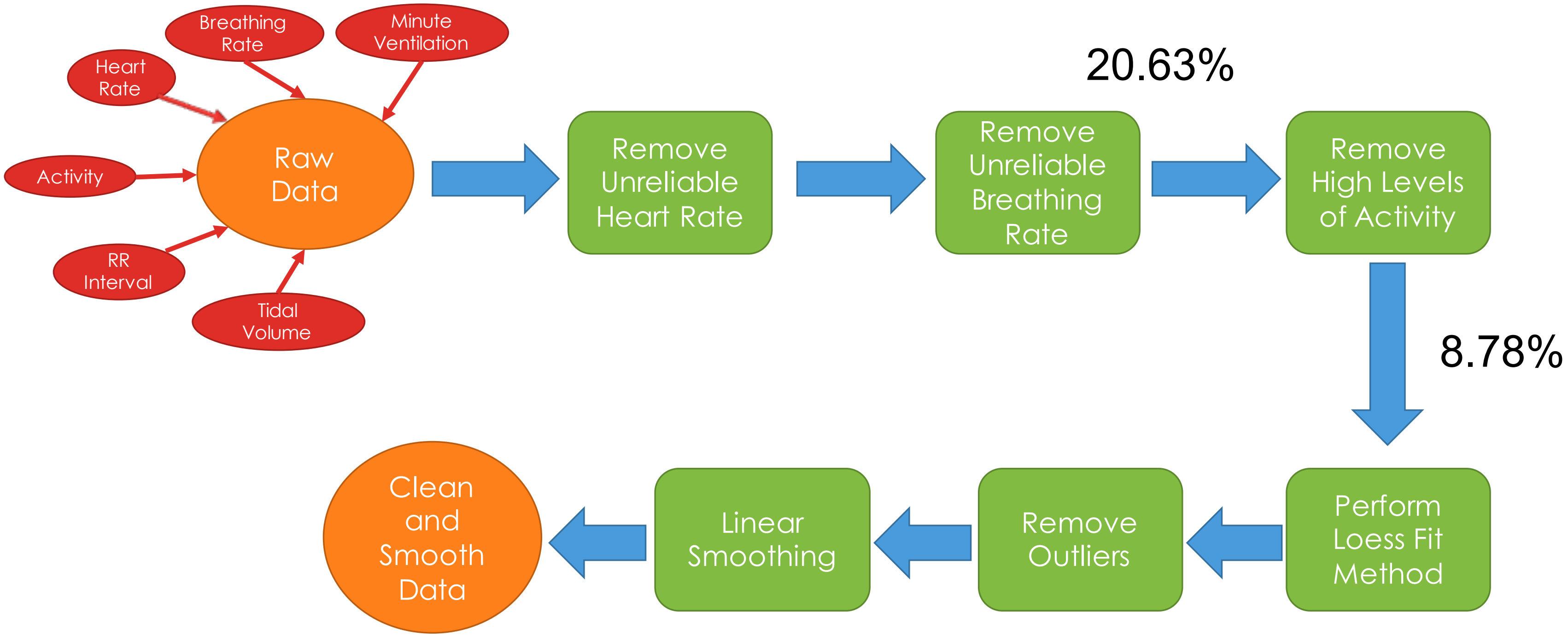








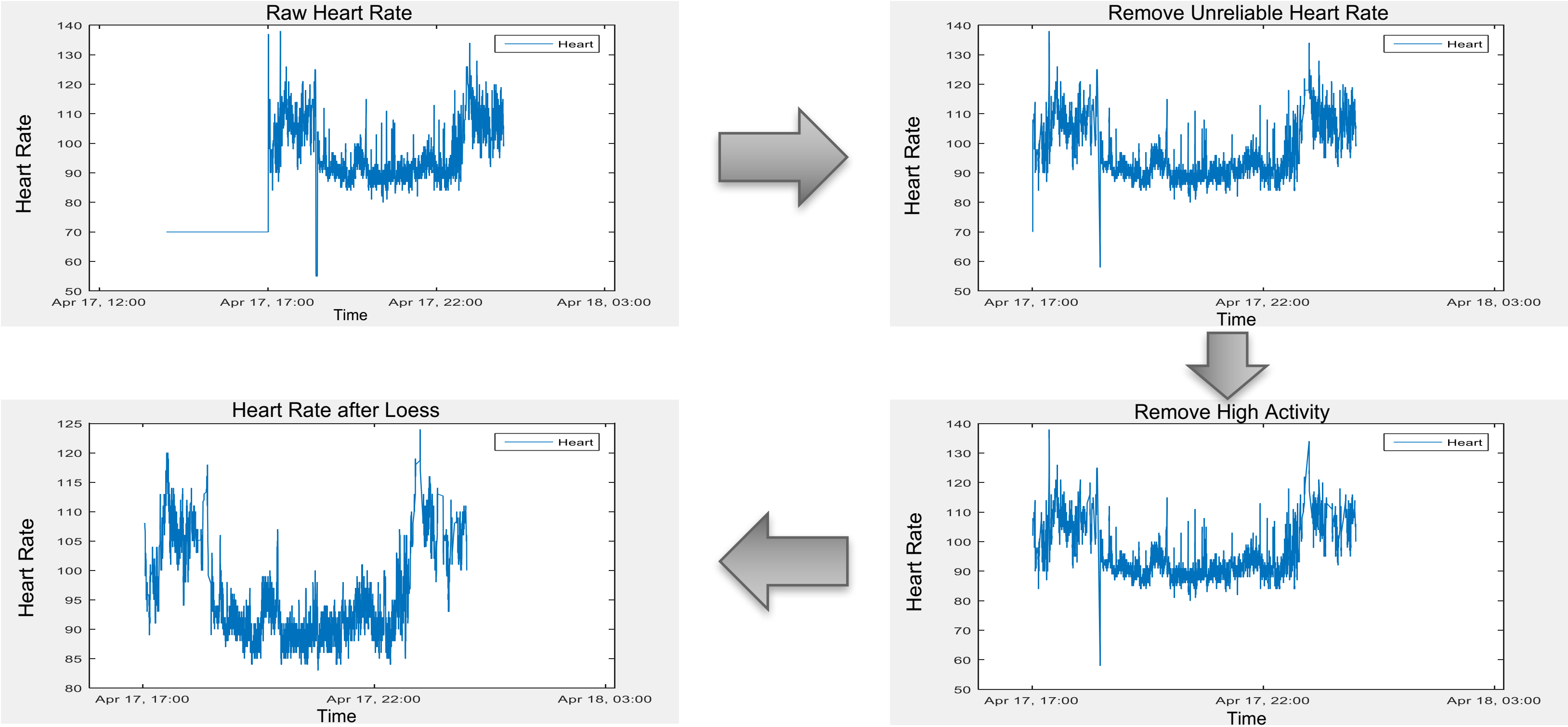
Better Approach



11.27%

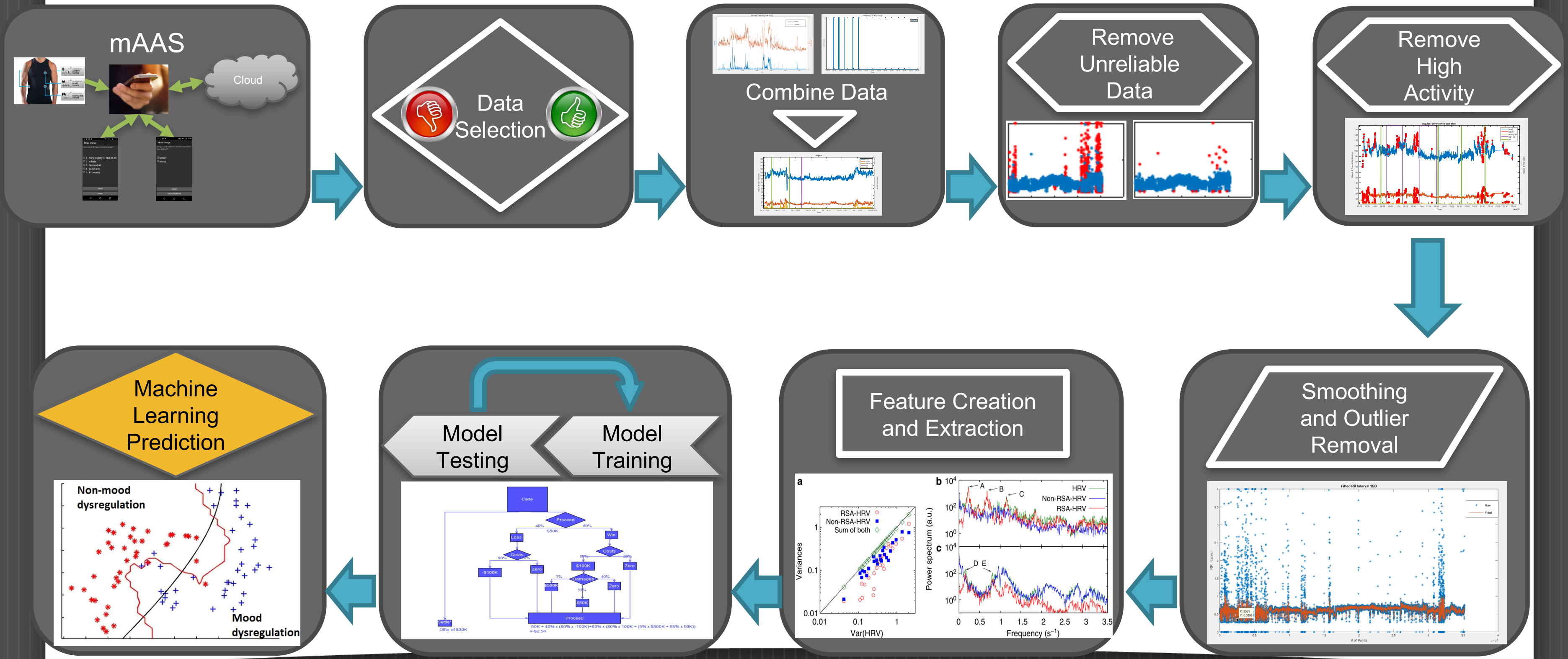
Total % of Data Removed: 40.68%

Better Approach



AMD’s Pipeline

Pipeline was implemented in MATLAB



Components

- AMD Pipeline
  - Different Approaches
  - Finalized Pipeline
  - Data Selection and Combination
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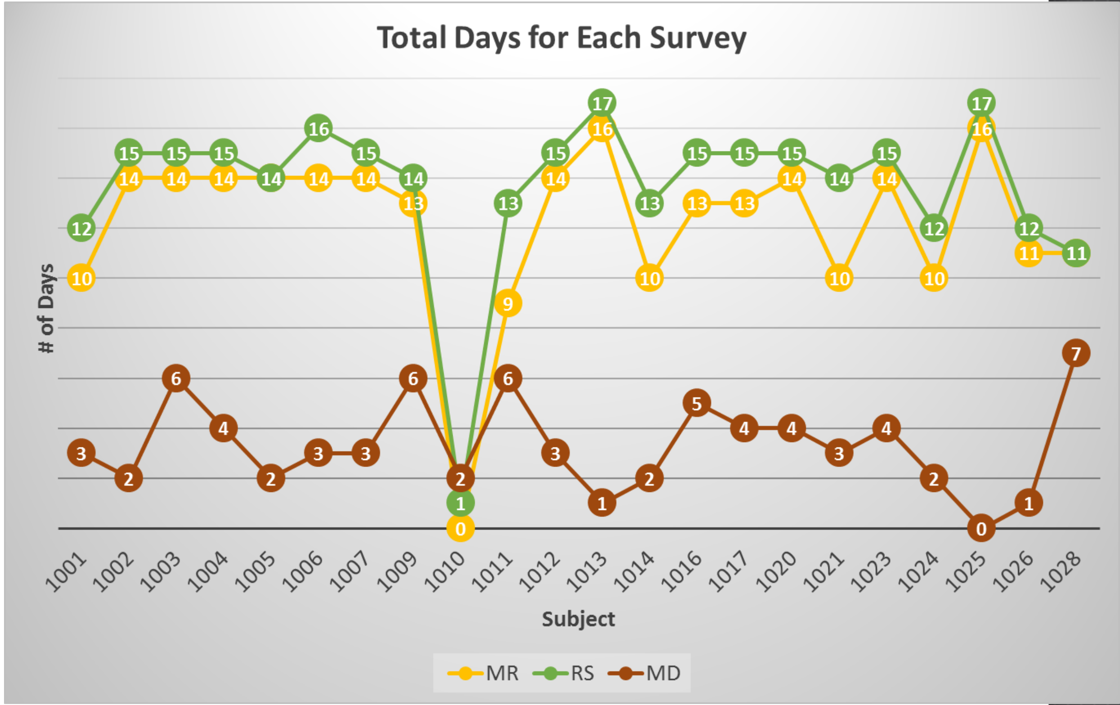
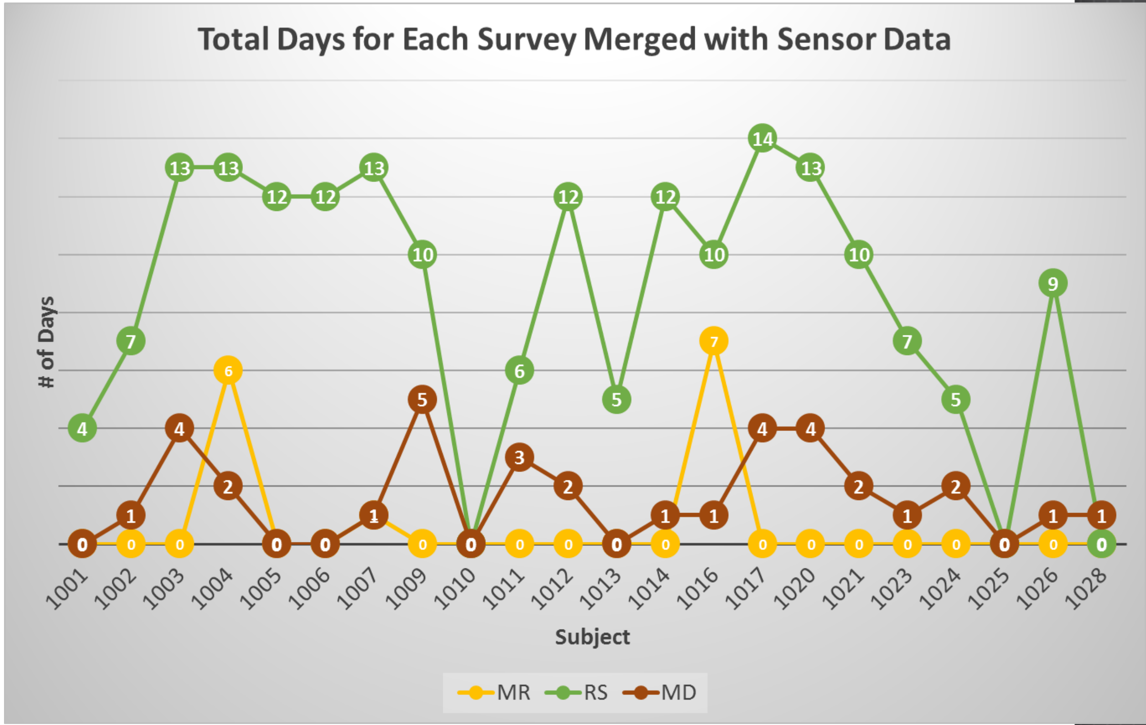
Data Selection

- During my research, a total of 22 participants' data available
  - Consisting of approximately two weeks of sequentially collecting physiological data and self-report mood data
- Only 16 were selected, must have:
  - 9 out of 14 days of self-report data
  - At least one mood dysregulation sample
  - At least one mood sample with corresponding sensor data
  - Valuable sensor data determined by status on sensor



Combine Data

- Hexoskin sensor data and survey data from two different sources
  - Need to be combined into one for machine learning model
- There were approx. 8.5 million sensor data records in DB
  - 1 record corresponds to 1 second
- After combining data, only 5601 sensor records matched in between mood survey start and end times for the 16 users

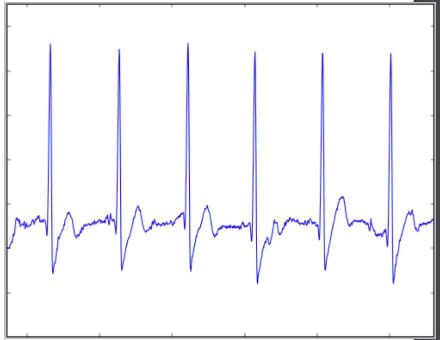


Combine Data (cont.)

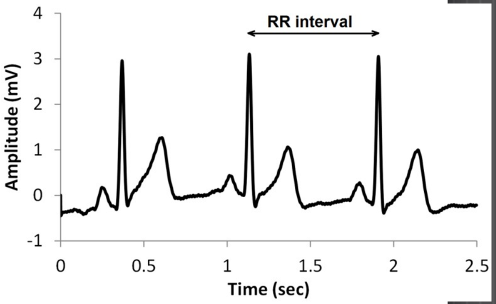
- Reasons?
  - Sensor was not worn by user during time of mood survey
  - Not good connection of sensor during time of survey
- After combining, more participants could not be used
  - Only 10 out of the 16 subjects now able to analyze
  - 6 of them did not have any corresponding survey with sensor data

Remove Unreliable Data

- Hexoskin sensor comes with attributes: Heart Rate Status and Breath Rate Status
  - Heart rate status is confidence of the ECG sensors
  - Breath rate status is confidence of RIP sensors
- If either of these status is unreliable, the data is removed, avg. removed 20.63% of 10 subjects
- This caused more participants to be removed from analysis
  - 7 subjects will continue for machine learning analysis

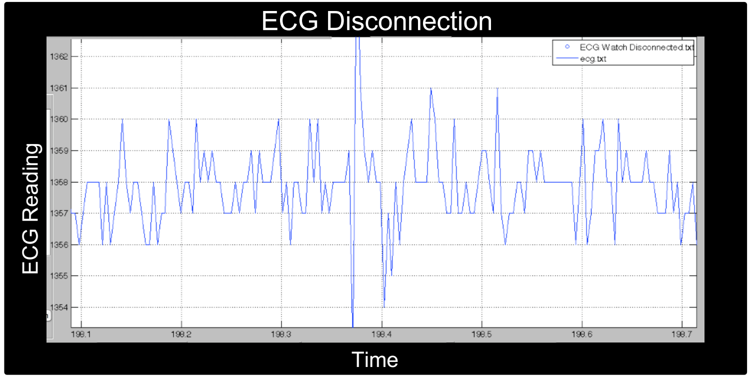


Normal Hexoskin ECG reading

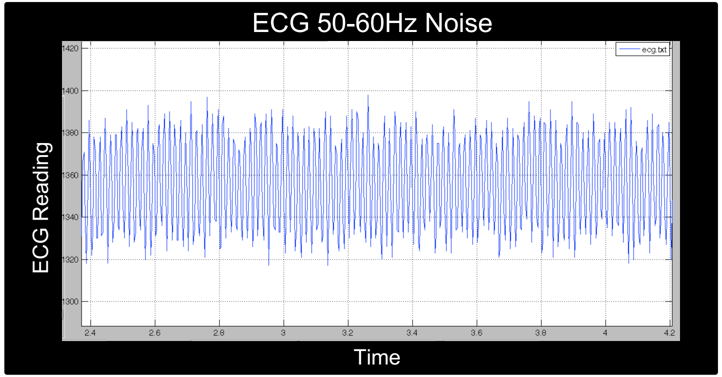


Examples of Unreliable Data

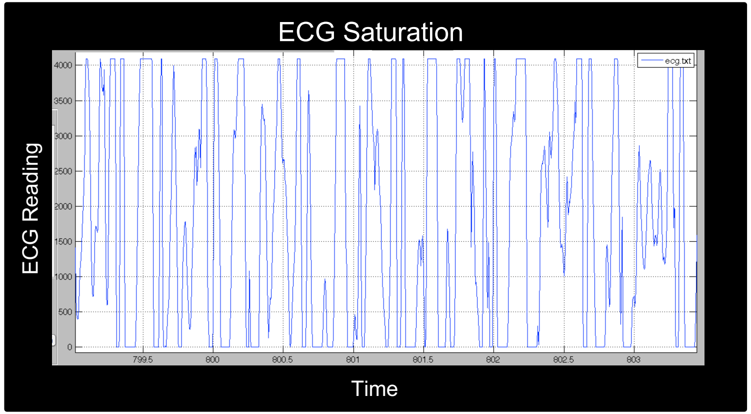
1.



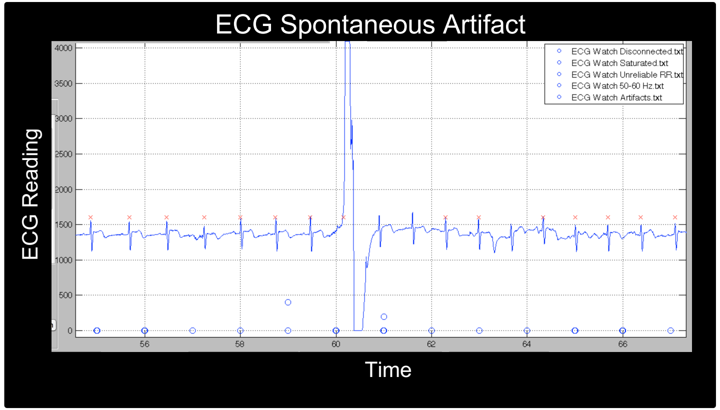
2.



3.



4.

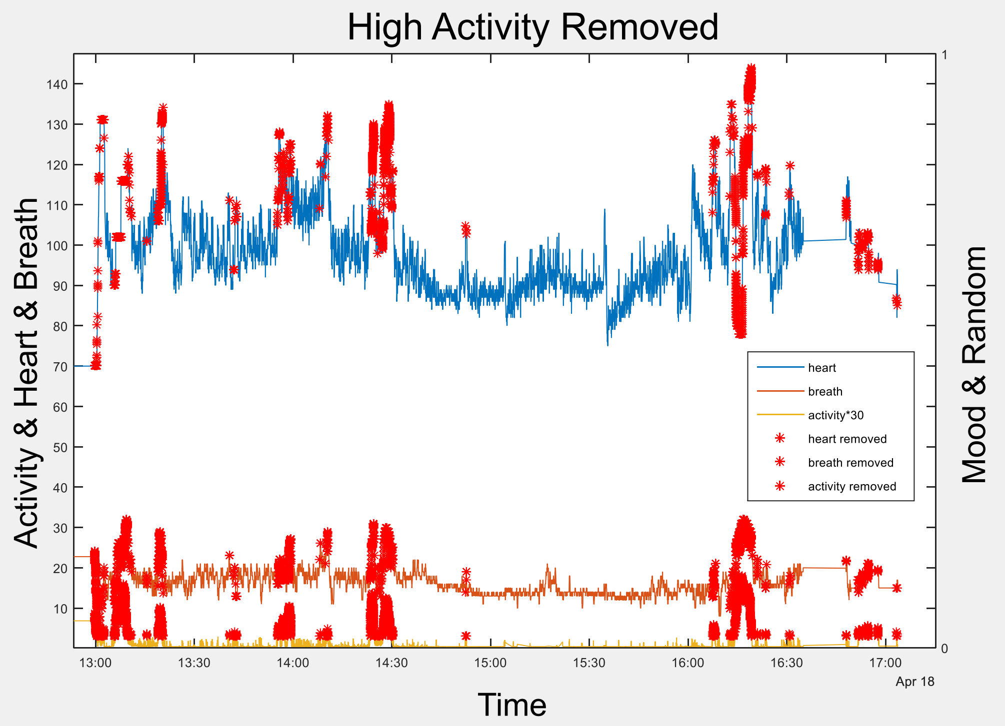


Remove High Activity

- When activity was high, sensor measurements were not reliable and often masks mood dysregulation

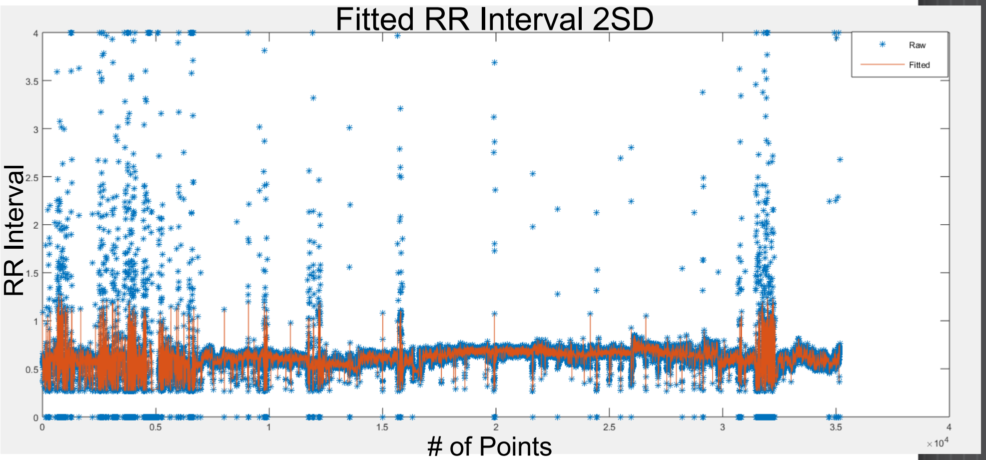
- Two minutes following physical activity were also removed, as described in literature
  - Physiology returns to baseline within two minutes after activity

- Approximately 8.78% removed of 7 subjects



Smoothing and Outlier Removal

- With remaining data, perform Loess Regression
  - Remove outliers 1SD and 2SD away from curve, suggested in literature
    - Better results obtained with 2SD
  - Perform regression imputation to fill in the outliers



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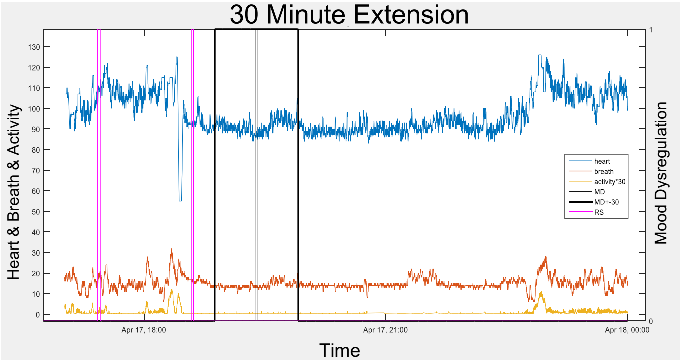
Feature Creation and Extraction

- 30 minute extension was created on start and end time of Mood Surveys
  - Now there are 74,042 mood samples instead of 5,601
- 9 Physiological Features were used in Prediction
  - Activity, RR Interval, Heart Rate, Breathing Rate, Minute Ventilation, Expiration, Inspiration, Tidal Volume, and Cadence



- 5 time attributes were created from the TimeStamp
  - Time Category(int), Only Hour, Only Hour and Minute, Only Time, and Time Category(String)
  - Time Categories: 5 < Morning < 11; 11 < Afternoon < 17; 17 < Evening < 23; 23 < Night < 5
- 11 Features were selected, the 9 Physiological Features and 2 Time Features

Training and Testing

- First, splitting the data sequentially was implemented
  - 80% for training, 10% for testing, and 10% for validation
- Next, 10 Crossfold Validation was used for Training and Testing
  - 10 crossfold had better results
  - Approximately 2-3% increase in accuracy
- Four models were implemented to compare results
  - Naïve Bayes, Bayesian Network, J48 Decision Tree, and Random Forest

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Prediction

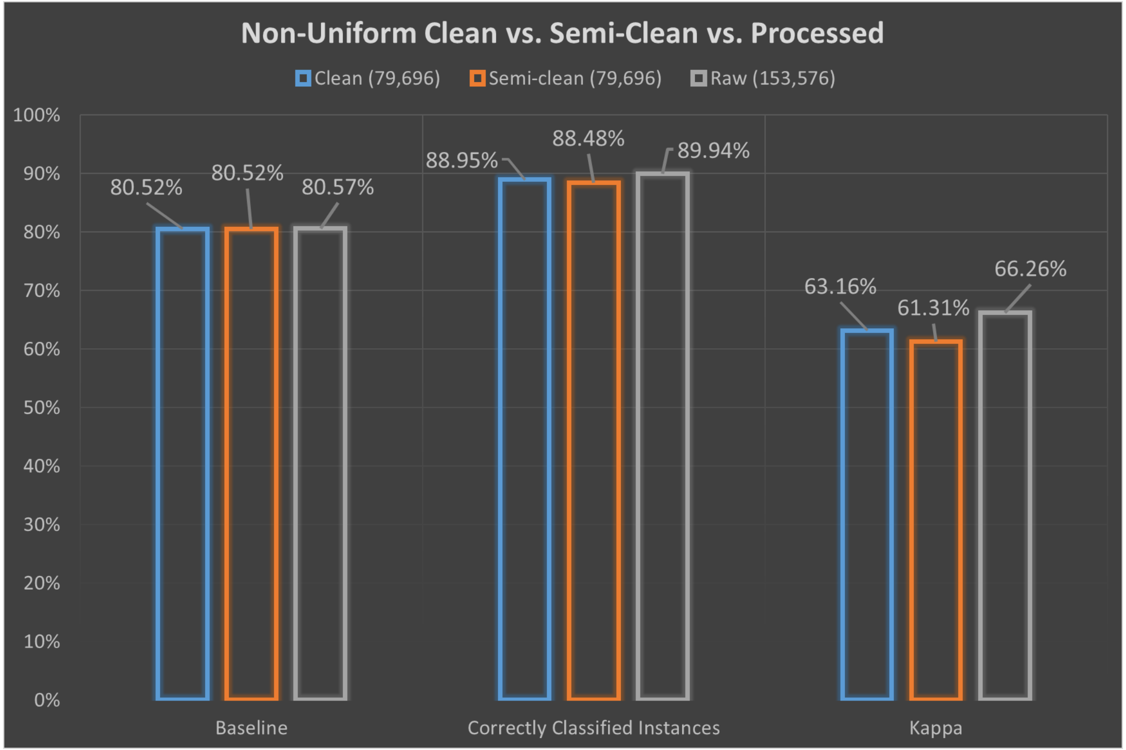
- Purpose: Use machine learning to predict when user is having mood dysregulation based off physiological features input
  - True Positive Labels are Mood Dysregulation Surveys self-initated by user from mAAS
- WEKA was used for machine learning prediction
- Evaluation: Confusion Matrix, Accuracy, Kappa, and ROC Area
  - Kappa > 0.5 acceptable, Overall Accuracy > .80

Components

- Introduction
- Related Work
- mAAS System Improvements
- Mood Study Overview
- AMD Pipeline
- Results and Model Comparison
  - Clean vs. Semi-Clean vs. Raw Data
  - Non-Balanced vs. Balanced Class
  - Time vs. Without Time Features
  - Model Comparison
  - Model Results Across All Subjects
  - Tree Structures and Best Features
- Knowledge Gained and Future Work

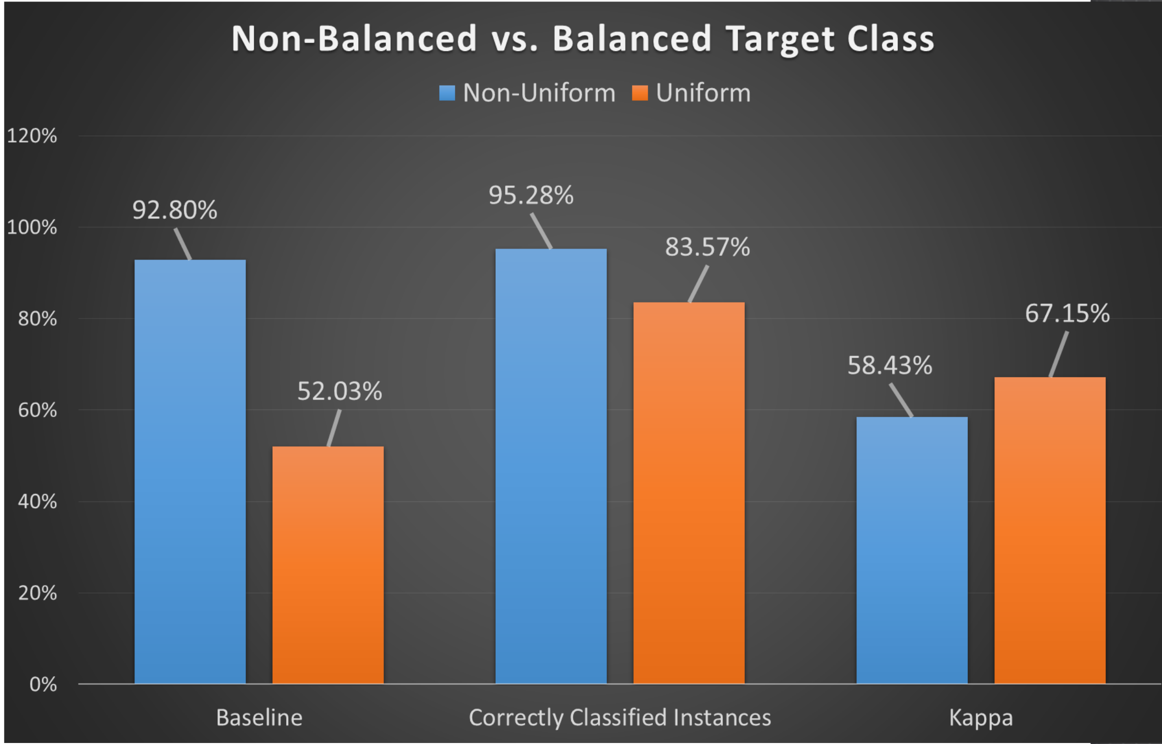
Clean vs. Semi-Clean vs. Raw Data

- Clean Kappa: 63.16%
- Semi Kappa: 61.31%
- Raw Kappa: 66.26%
- Clean > Semi-Clean
- Raw > Clean
- Raw has best result
- Raw is used in further analysis



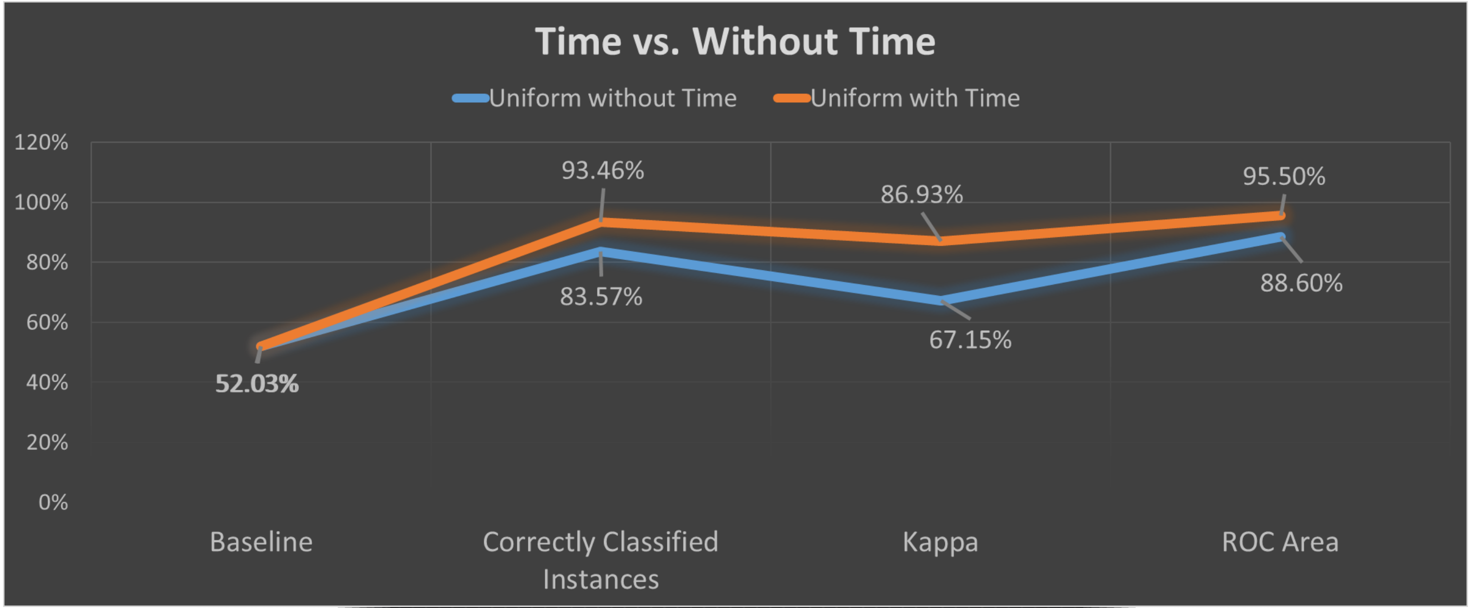
Non-Balanced vs. Balanced Class

- Without uniform
  - Baseline: 92.80%
  - Accuracy: 95.28%
  - Does not make sense
- Uniform has higher Kappa results

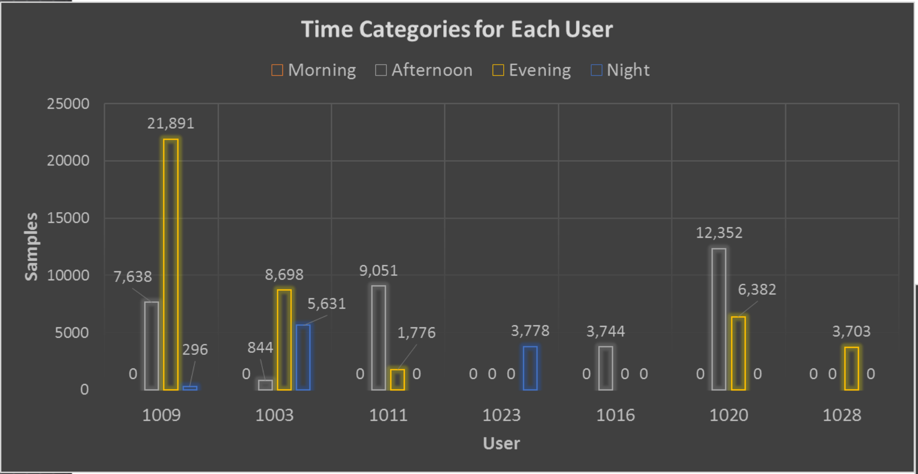


Time vs. Without Time

- Results improved approximately 11%
  - With my custom created features, Hour of Day (Integer) and Time Category (Integer)

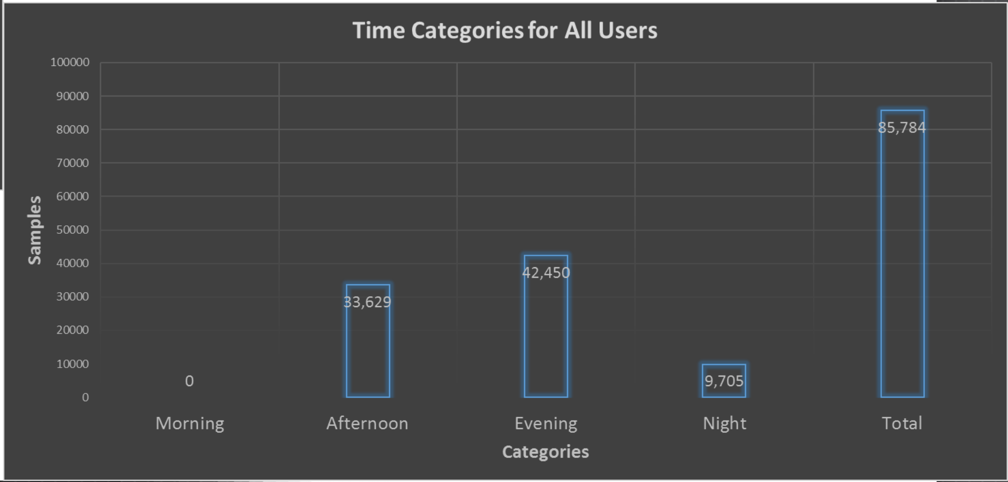


Discussion

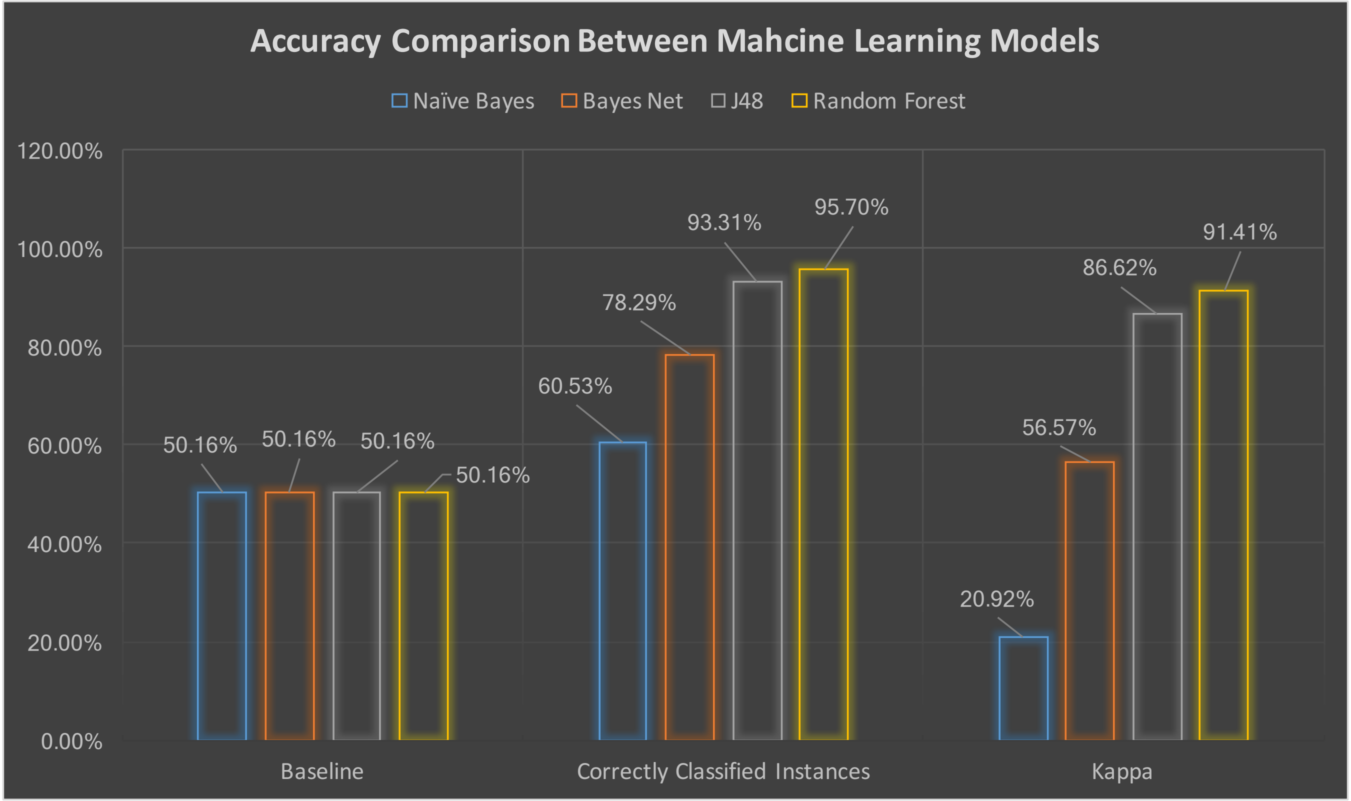


- For each user, most mood dysregulation happens during the Afternoon and Evening Categories

- For all users, you can see the frequency distribution for Afternoon and Evening categories, 39.20% and 49.48% respectively



Bayes vs. J48 vs. Random Forest Accuracy



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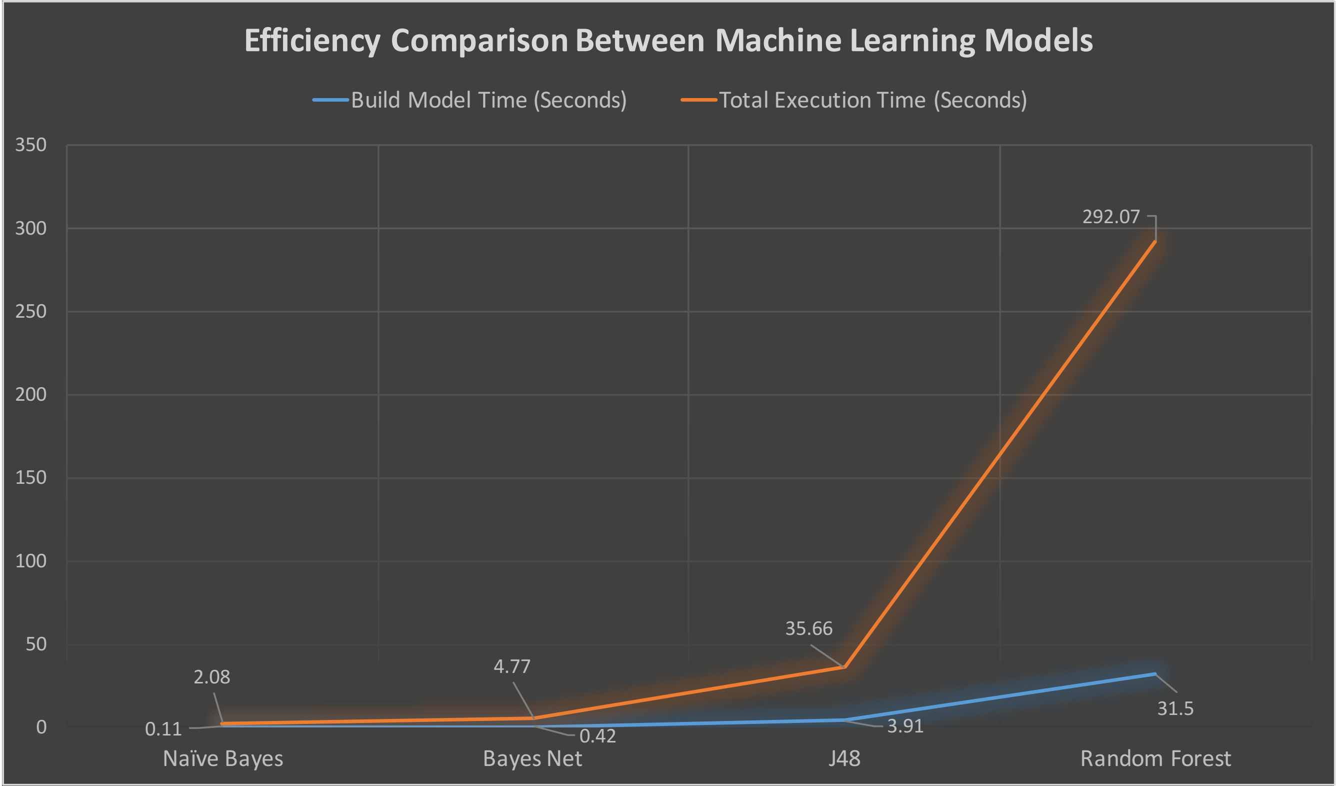
Bayes vs. J48 vs. Random Forest Efficiency



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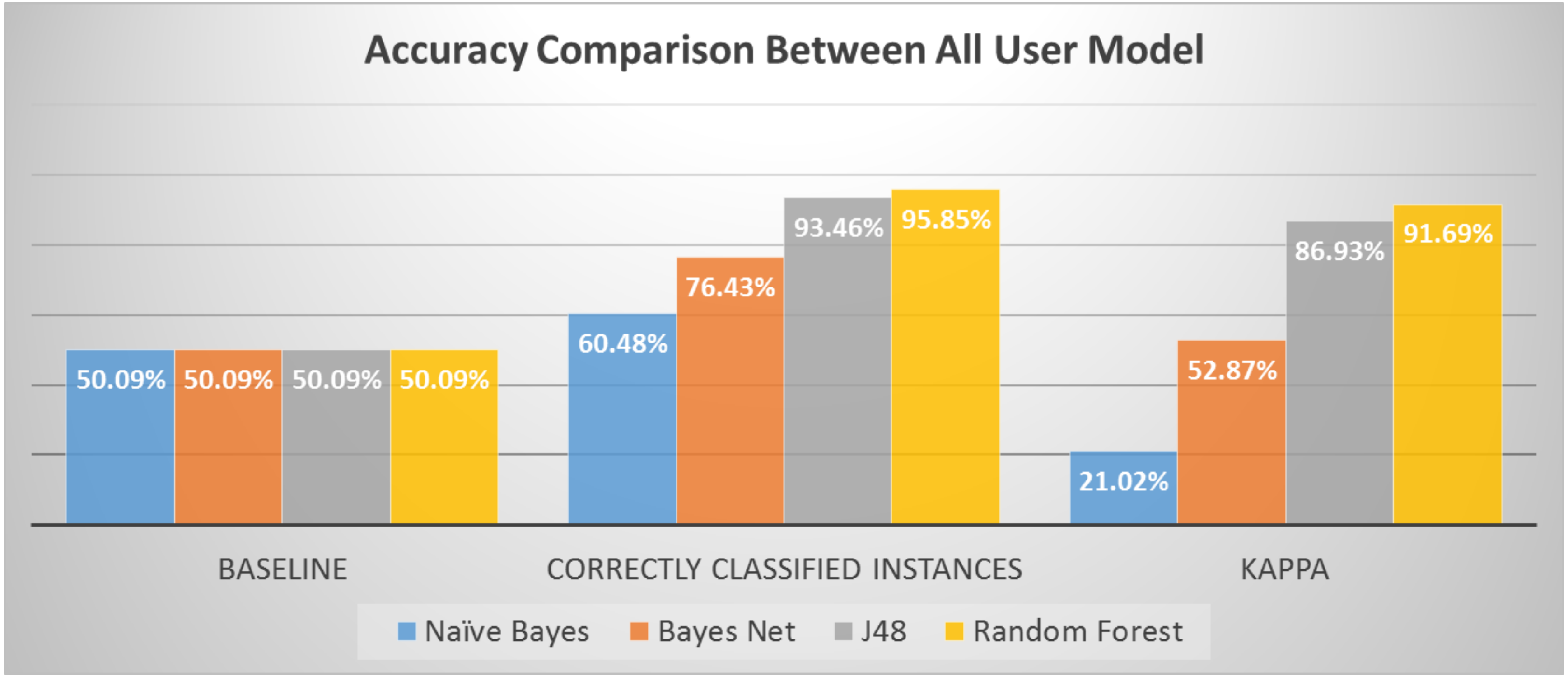
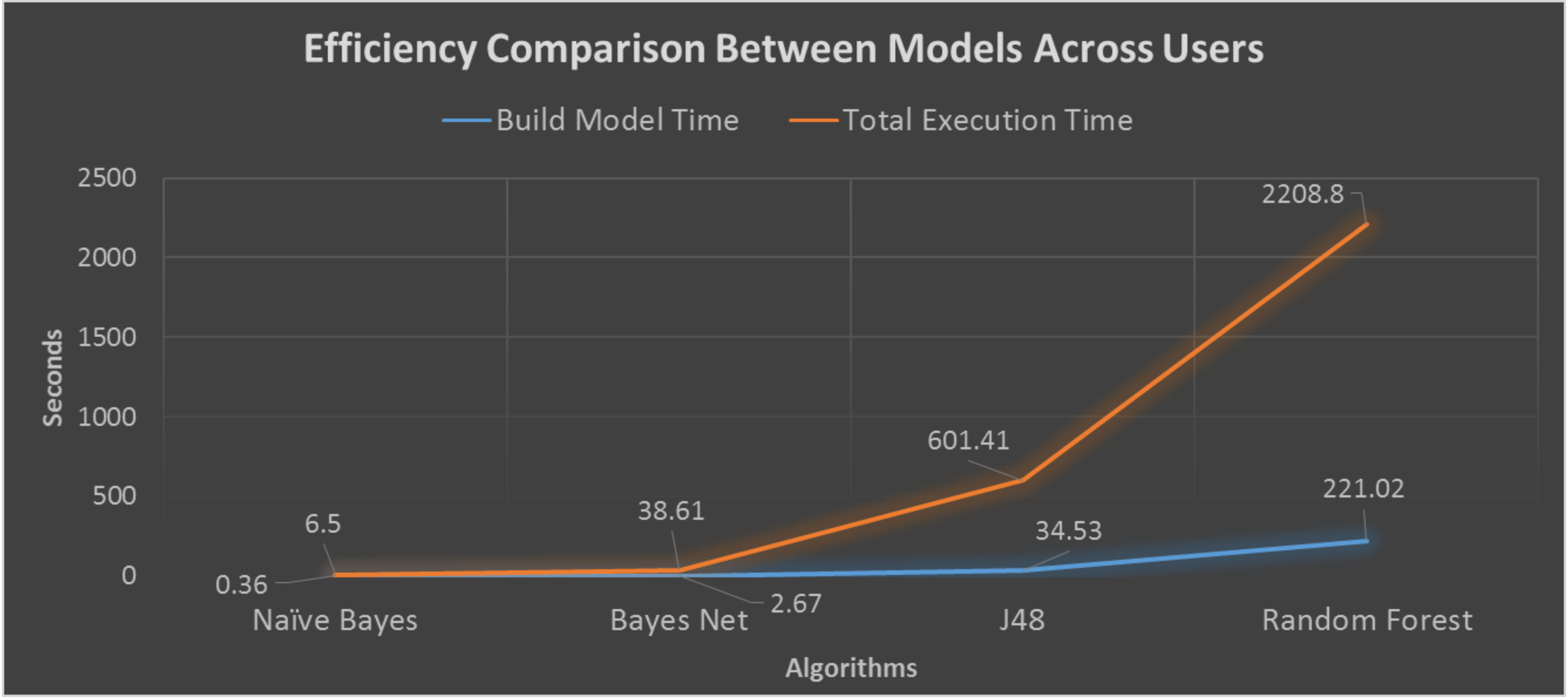
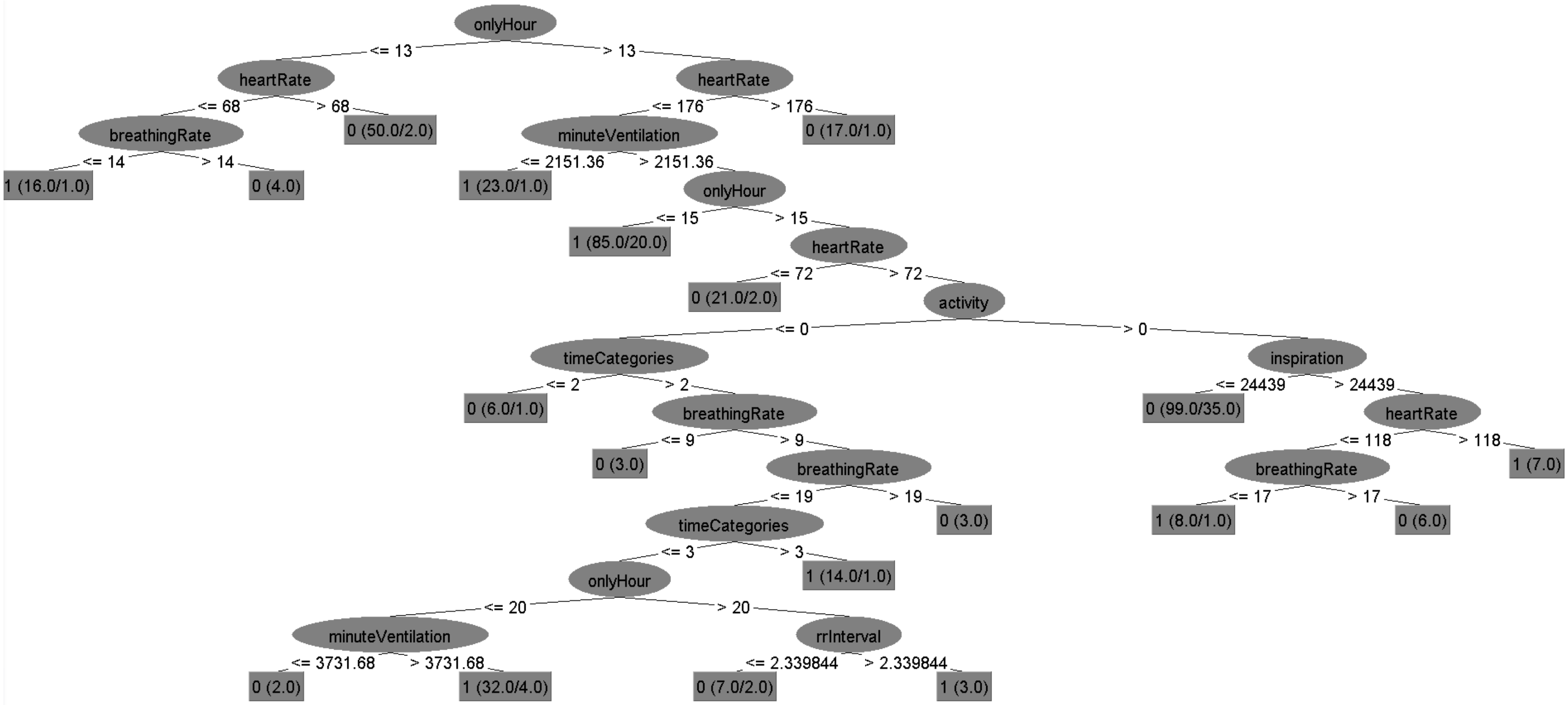
Accuracy Across All Subjects



Efficiency Across All Subjects



Tree Structure for One User



Tree Structure for All Users

- Time Categories is most valuable
- Next is inspiration and expiration
- Proceeding is Heart rate and Hour of Day

```
J48 pruned tree
------------------

timeCategories <= 1: 0 (76001.0)
timeCategories > 1
|   expiration <= 26165
|   |   inspiration <= 26202
|   |   |   heartRate <= 179
|   |   |   |   onlyHour <= 13
|   |   |   |   |   heartRate <= 68
|   |   |   |   |   |   onlyHour <= 1
|   |   |   |   |   |   |   expiration <= 7355
|   |   |   |   |   |   |   |   breathingRate <= 14
|   |   |   |   |   |   |   |   |   minuteVentilation <= 6706.4
|   |   |   |   |   |   |   |   |   |   activity <= 0
|   |   |   |   |   |   |   |   |   |   |   onlyHour <= 0
|   |   |   |   |   |   |   |   |   |   |   |   minuteVentilation <= 3439.52: 0 (1425.0)
|   |   |   |   |   |   |   |   |   |   |   |   minuteVentilation > 3439.52
|   |   |   |   |   |   |   |   |   |   |   |   |   heartRate <= 60
|   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate <= 7: 1 (2006.0/1.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate > 7
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   minuteVentilation <= 6148.64: 0 (69.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   minuteVentilation > 6148.64
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   heartRate <= 56: 1 (354.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   heartRate > 56
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   rrInterval <= 1.148438: 0 (17.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   rrInterval > 1.148438: 1 (17.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   heartRate > 60
|   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate <= 6
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   tidalVolume <= 717.12: 0 (63.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   tidalVolume > 717.12
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   rrInterval <= 0.800781
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate <= 5: 0 (2.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate > 5: 1 (12.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   rrInterval > 0.800781: 1 (169.0/1.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate > 6: 0 (650.0)
|   |   |   |   |   |   |   |   |   |   |   onlyHour > 0
|   |   |   |   |   |   |   |   |   |   |   |   tidalVolume <= 252.32
|   |   |   |   |   |   |   |   |   |   |   |   |   minuteVentilation <= 2204.48
|   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate <= 6: 0 (35.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   breathingRate > 6
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   heartRate <= 61
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   heartRate <= 54
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   minuteVentilation <= 1938.88: 1 (42.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   minuteVentilation > 1938.88: 0 (40.0)
|   |   |   |   |   |   |   |   |   |   |   |   |   |   |   |   heartRate > 54
```

Components

- Introduction
- Related Work
- mAAS System Improvements
- Mood Study Overview
- AMD Pipeline
- Results and Model Comparison
- Knowledge Gained and Future Work

Knowledge Gained

- Creating time categories for each day improves accuracy of AMD by more than 10%
- Mood dysregulation happens during afternoon and evening categories 60.54% more than the morning and night categories
- Using pre-processed data from Hexoskin achieved higher accuracy than using cleaned data
- Accuracy and Efficiency are consistent across Single User Model and All User Model
  - J48 would be the model of choice since accuracy is high, similar to Random Forest, and 10 times faster than Random Forest

More Knowledge Gained

- For all user model, most important attribute is Time Category
  - The second most important attribute is Inspiration
- For single user model, most important attribute is Hour of Day
  - The second most important attribute is Inspiration
- Out of physiological measurements
  - Inspiration is the most valuable measure for mood
  - Heart Rate is second most valuable measure for mood

Future Work

- Implement AMD on a mobile device
  - Current the pipeline is on a server with unlimited resources
- Implement Deep Learning pipeline and compare it to AMD's results
  - Next, implement the deep learning pipeline on a mobile device
- More users have collected data since my analysis
  - My research can be duplicated on the new users
- More surveys can be analyzed for all users
  - There are 62,353 Random Prompt Surveys out of 69,316 surveys this research analyzed
- My pipeline can be used on 4 other Psychology studies being implemented
  - Mood Toolkit Study, TigerAware Study, SLU HIV Study, and Alcohol Craving Study

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and

Professor Tim Trull

Discussion