Capstone Report

Predicting Emotional States Using Wearable Devices

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Outline

- Background
- Data Description
- Problem Definition
- Modeling
- Analysis
- Conclusion
- Challenges & Next Steps

Background

1. 1 in 5 Americans wear a fitness tracker to monitor factors important for a healthy life[1]

- sleep
- physical activity
- cardiovascular health

2. Emotions also contribute to overall well-being

- Chronic negative emotions can be detrimental to both mental and physical health[2]

3. Emotion detection technology could help users understand and relieve negative mood states

1. https://www.pewresearch.org/fact-tank/2020/01/09/about-one-in-five-americans-use-a-smart-watch-or-fitness-tracker/
2. Salovey, Peter, et al. "Emotional states and physical health." *American psychologist* 55.1 (2000): 110.

Can affective states be reliably recognized

From

Fitbit Data

From

Fitbit Data

Psychological Data

Demographic

Physical Health

Data Description

Demographics

Age
Sex
Income
Marital Status
Children
BMI

Activity Tracker

Steps
Heart Rate
Sleep

Psychometric

Neuroticism
Extraversion
Ideal/Actual Emotion
Activation/Inhibition
Novelty Seeking
Life Satisfaction
Impulsiveness

Data Description

How ***calm, at rest, or serene***, do you feel right now?

Not at all Extremely

enthusiastic, excited, elated?

fearful, hostile, nervous

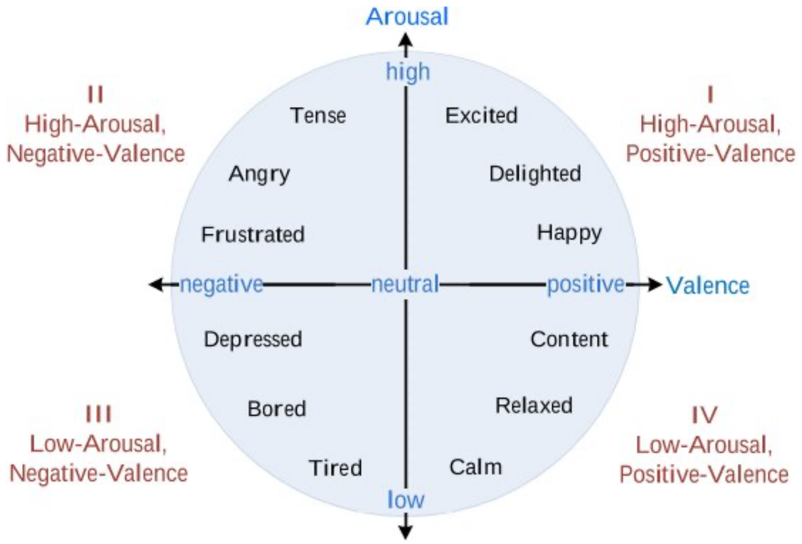
dull, sleepy, sluggish?

quiet, still, passive?

happy, satisfied, content?

sad, lonely, unhappy?

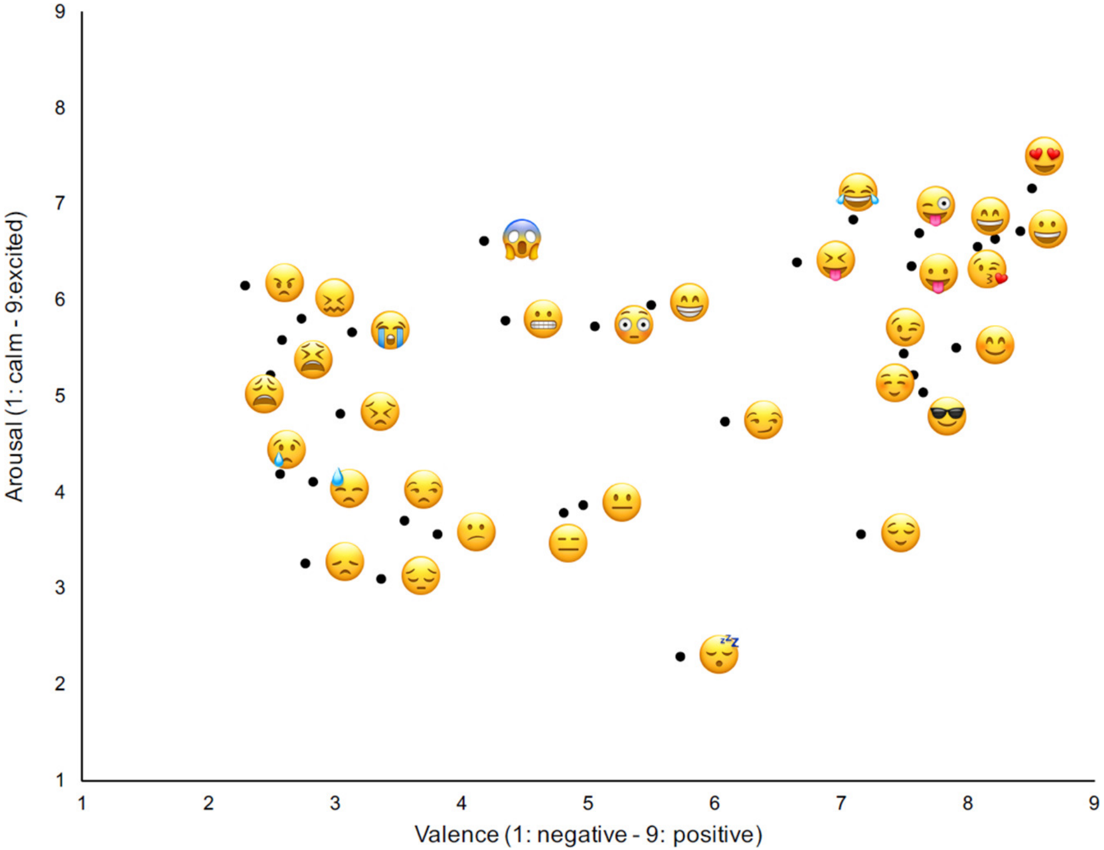
aroused, surprised, or astonished?



Problem Definition

`**Emotion**` is a psychological construct composed of several features or dimensions

We decided to reduce the target variable into a single dimension: **Valence**



Jaeger, S. R., Roigard, C. M., Jin, D., Vidal, L., & Ares, G. (2019)

We would like to know two things:

1. Is this subject experiencing a positive or negative emotional state?

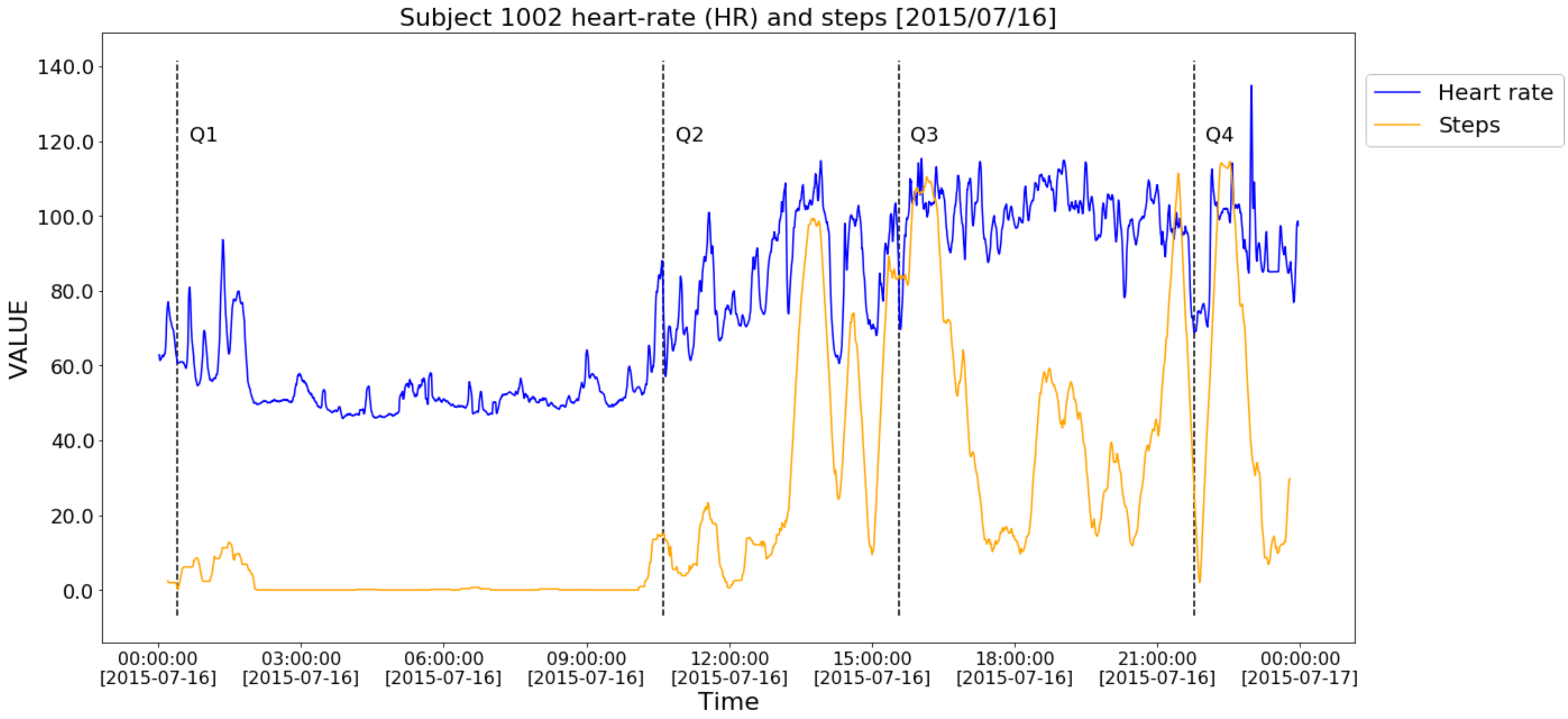
$$\text{Positive Negative Emotion} = \begin{cases} 1, & \max(la\_n_{s,i}, n_{s,i}, ha\_n_{s,i}) \geq \max(la\_p_{s,i}, p_{s,i}, ha\_p_{s,i}) \\ 0, & \text{otherwise} \end{cases}$$

2. Is this subject happier or unhappier than his/her baseline level?

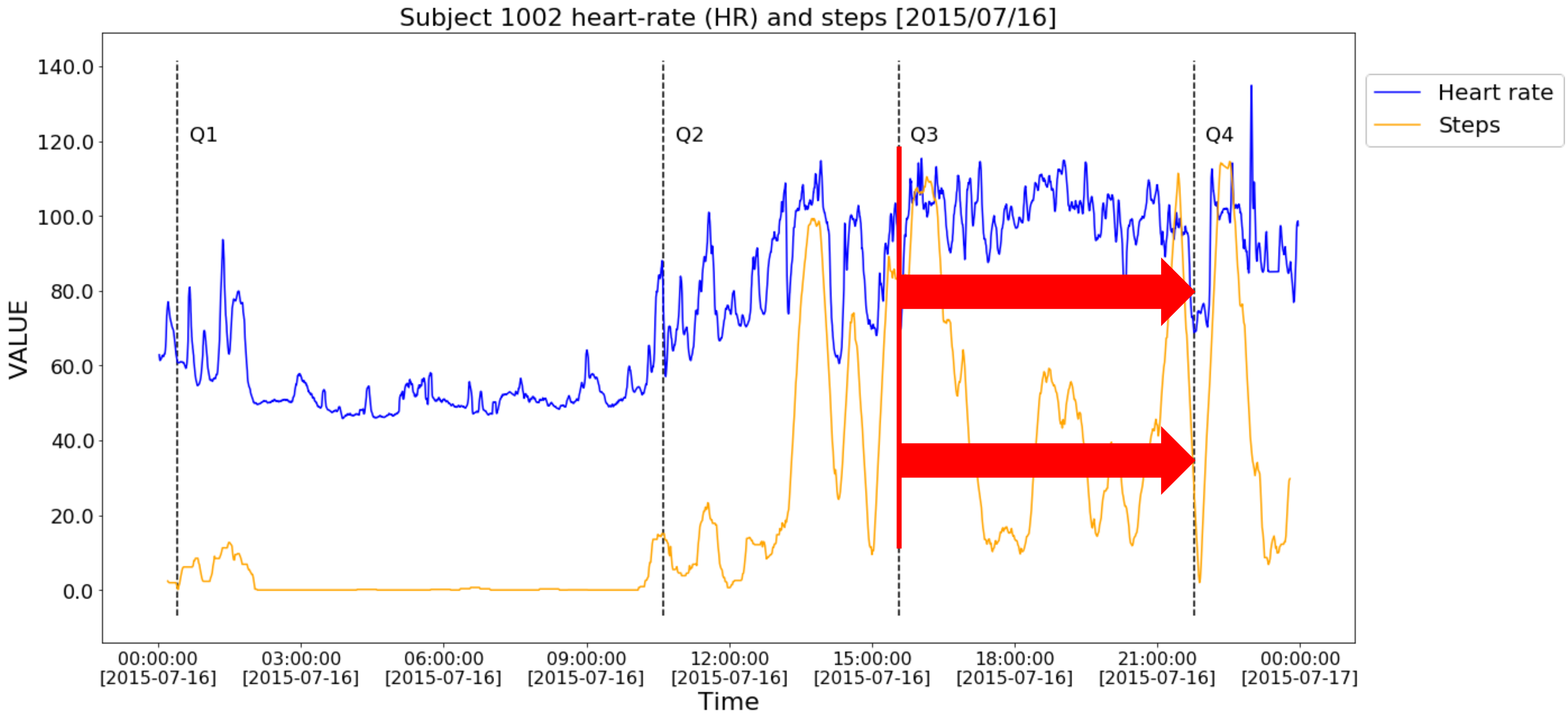
$$\text{Valence} = \frac{\text{High Arousal Positive}_{s,i} + \text{Low Arousal Positive}_{s,i} + \text{Positive}_{s,i}}{3} - \frac{\text{High Arousal Negative}_{s,i} + \text{Low Arousal Negative}_{s,i} + \text{Negative}_{s,i}}{3}$$

$$\text{Normalized valence} = Valence_{s,i} - Median(Valence_s)$$

$$\text{Normalized valence (binary)} = \begin{cases} 1, & \text{Normalized Valence}_{s,i} > Median(Valence_s) \\ 0, & \text{otherwise} \end{cases}$$



Subject 1002 heart-rate (HR) and steps [2015/07/16]
Heart rate
Steps
Q1
Q2
Q3
Q4
VALUE
140.0
120.0
100.0
80.0
60.0
40.0
20.0
0.0
00:00:00 [2015-07-16]
03:00:00 [2015-07-16]
06:00:00 [2015-07-16]
09:00:00 [2015-07-16]
12:00:00 [2015-07-16]
15:00:00 [2015-07-16]
18:00:00 [2015-07-16]
21:00:00 [2015-07-16]
00:00:00 [2015-07-17]
Time



Subject 1002 heart-rate (HR) and steps [2015/07/16]
VALUE
140.0
120.0
100.0
80.0
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Q1
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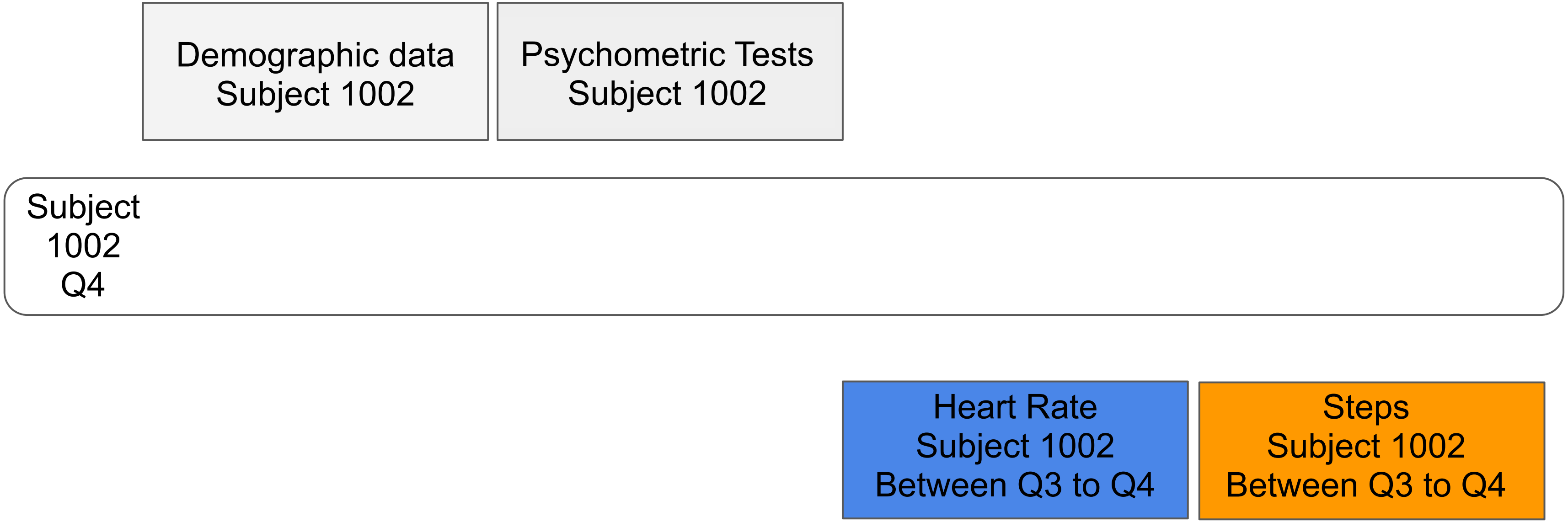
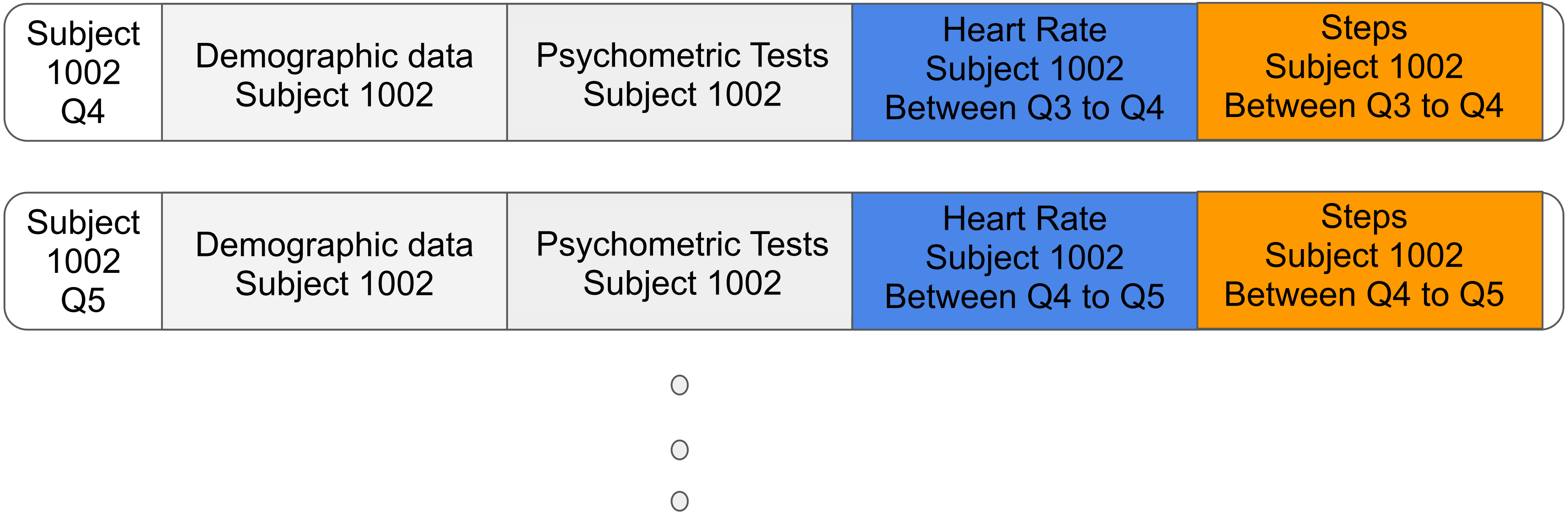
18:00:00 [2015-07-16]
21:00:00 [2015-07-16]
00:00:00 [2015-07-17]
Time


Demographic data
Subject 1002
Psychometric Tests
Subject 1002
Subject
1002
Q4
Heart Rate
Subject 1002
Between Q3 to Q4
Steps
Subject 1002
Between Q3 to Q4


Subject 1002 Q4
Demographic data Subject 1002
Psychometric Tests Subject 1002
Heart Rate Subject 1002 Between Q3 to Q4
Steps Subject 1002 Between Q3 to Q4
Subject 1002 Q5
Demographic data Subject 1002
Psychometric Tests Subject 1002
Heart Rate Subject 1002 Between Q4 to Q5
Steps Subject 1002 Between Q4 to Q5

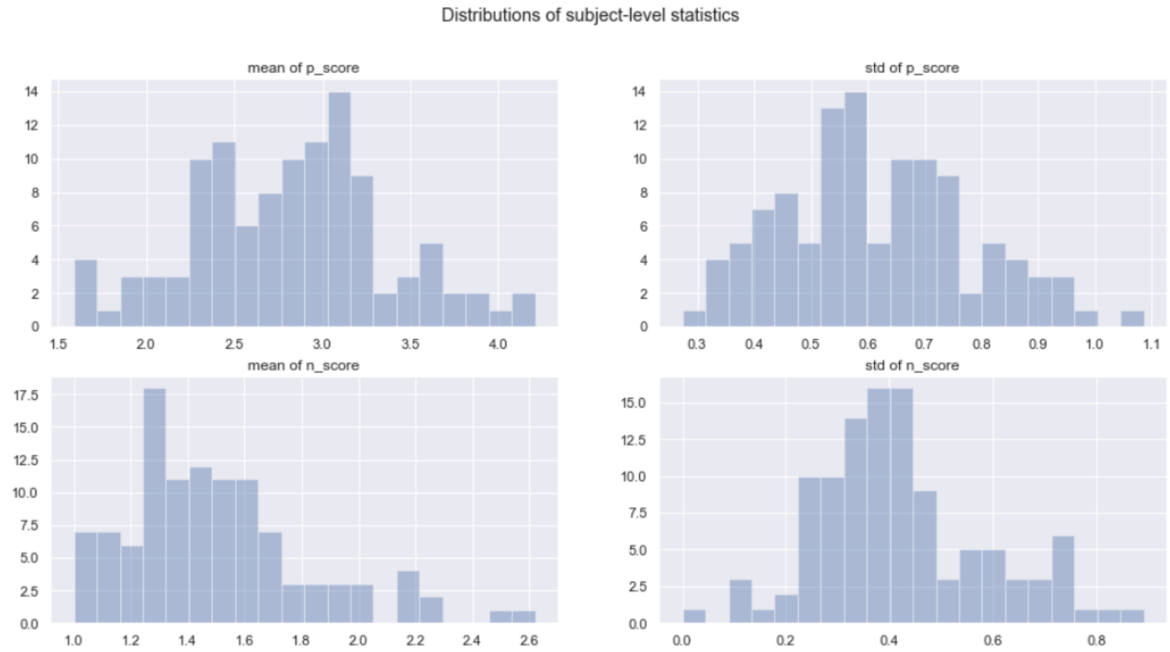
Modeling Outline

1.Preprocessing → 2.EDA → 3.Feature Engineering → 4.Modeling → 5.Evaluation

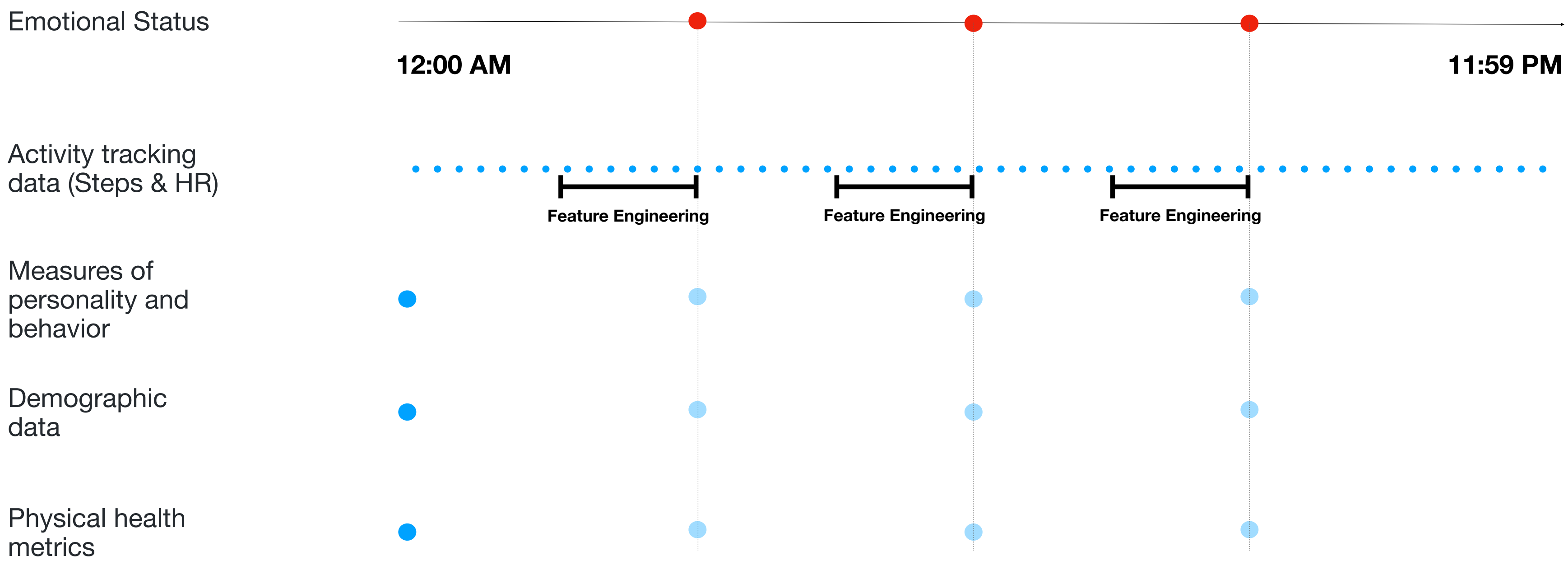
EDA – By subject analysis

The subject level statistics indicates there is huge variance across subjects.

p_score = mean(la_p, p, ha_p)
n_score = mean(la_n, n, ha_n)



Feature Engineering



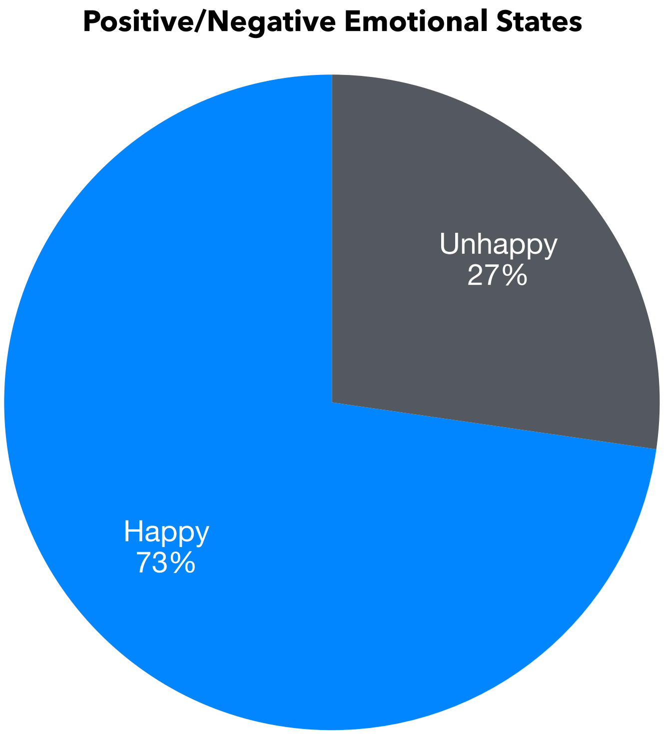
Feature Engineering – Steps related features

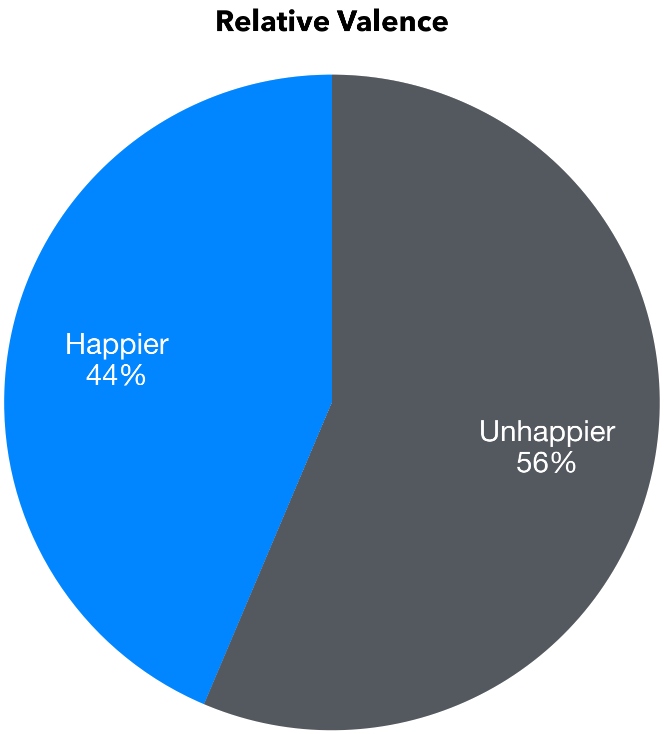
- Statistics: max, min, mean, std
- Move Rate: The # of minutes with step > 0 / total minutes
- Active Rate: The # of minutes with step > 10 / total minutes
- Very Active Rate: The # of minutes with step > 20 / total minutes
- Running Rate: The # of minutes with step > 30 / total minutes

Feature Engineering – Heart Rate related features

- Statistics: max, min, mean, std
- Resting Rate: The # of minutes with HR < 30 percentile heart rate > 0 / total minutes
- Moderate Rate: The # of minutes with HR > 50 percentile heart rate > 0 / total minutes
- Very Active Rate: The # of minutes with HR > 80 percentile heart rate > 0 / total minutes
- SDNN: Standard deviation of heartbeat intervals
- pHR2: Percentage of the difference between adjacent HR greater than 2
- rMSSD: Root of mean squared HR change
- Highest HR
- Lowest HR
- l_h: Lowest HR / Highest HR
- CR: Highest HR / Highest HR so far

Modeling – Problem Setting – Problem Definition





Type 1: Split by Subject

Type 2: Stratified Split

Predict for new user

Predict for current user

Training Set

Test Set

Type 1: Only use Fitbit data

Fitbit Data

Type 2: Use all data we have

Fitbit Data

Psychological Data

Demographic

Physical Health

1. **Down Sample the Majority Class**

2. **Up Sampling the Minority Class**

3. **SMOTE** - Synthetic Minority Over-sampling Technique

4. Assign Class Weight to Loss Function

Evaluation – Positive/Negative Emotion Results

	Scenario	Data	Sampling Technique	Recall	Precision	F1
1	Current Users	Activity Tracking (Fitbit)	SMOTE	0.550	0.347	0.425
2	New Users	Activity Tracking (Fitbit)	Assign Class Weight to Loss Function	0.419	0.228	0.295
3	Current Users	All Data	Assign Class Weight to Loss Function	0.626	0.482	**0.544**
4	New Users	All Data	SMOTE	0.870	0.260	0.399

In comparison, random guess gives an precision of 0.273

Evaluation – Relative Valence Prediction Results

	Scenario	Data	Sampling Technique	Recall	Precision	F1
1	Current Users	Activity Tracking (Fitbit)	-	0.578	0.617	0.596
2	New Users	Activity Tracking (Fitbit)	-	0.699	0.558	0.617
3	Current Users	All Data	-	0.877	0.590	**0.705**
4	New Users	All Data	-	0.959	0.555	0.703

In comparison, random guess gives an precision of 0.564

Evaluation – Positive/Negative Emotion Results

	Scenario	Data	Sampling Technique	Recall	Precision	F1
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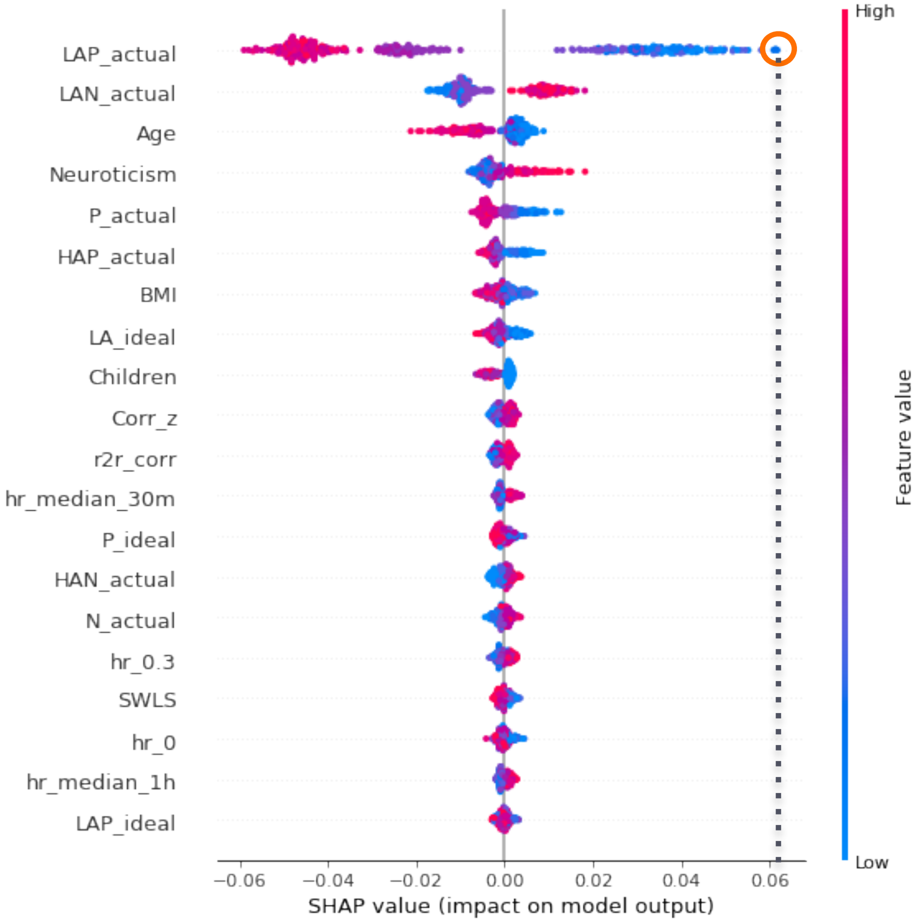
Modeling – Results



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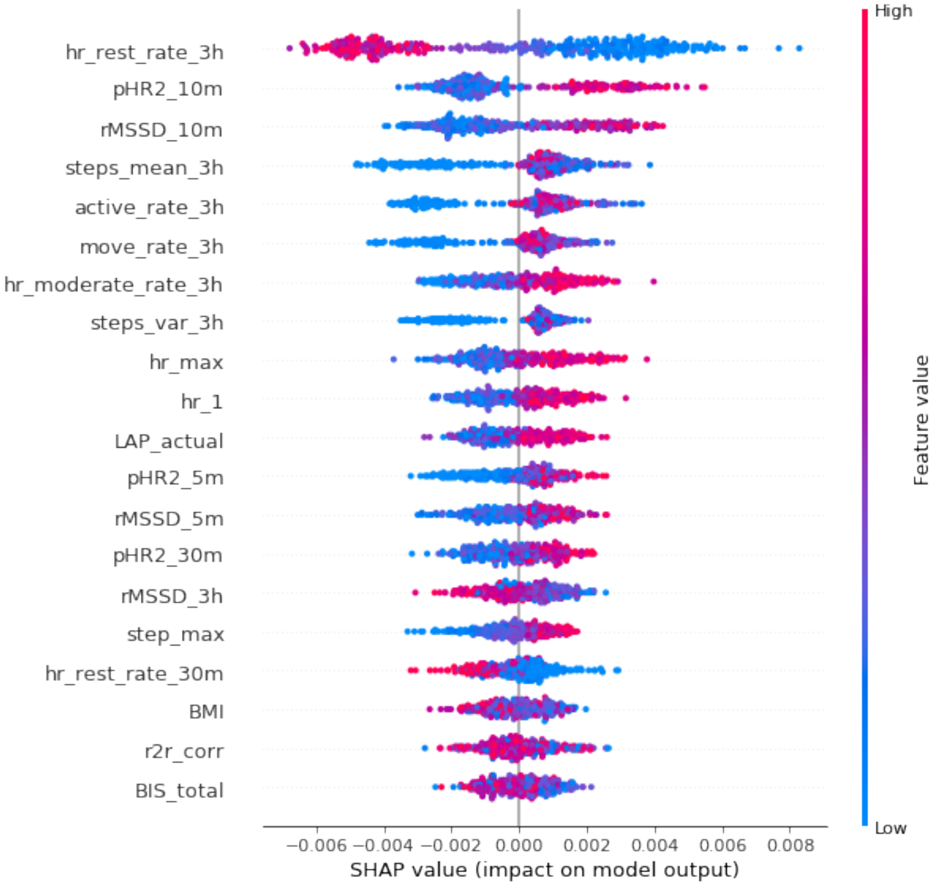
Modeling – Results



Conclusions

1. In general, the data (wearable data, psychological data, health metrics and demographic data) would help the prediction of emotional states for current users.

2. Psychological features and age have a significant correlation on absolute level of valence. While wearable data reflects relative valence, especially heart rate related feature.

3. It is hard to predict emotional states for a new user. The pattern we have learnt from current users could actually harm the prediction for new users.

Challenges and Next Steps

Challenges:

1. Small data
2. Missing data
3. Complexity of emotion and variation between subjects

Next:

1. Keep Connecting with Stakeholder, ask for their needs
2. Incorporating neuroimaging features
3. Try Ensemble techniques

Thanks!

Q&A