### BIOMEDICAL ENGINEERING

### BACKGROUND

Fitbit data such as heart rate and step count are granular markers of status that can serve as indicators of mobility, which is an recovery after marker of important Their continuous measurement stroke. provide accurate assessments of mobility, and by extension, predictors of health and functional status. The goal of this work was to derive metrics from Fitbit data that could be used to replace in-clinic tests and serve as a more dynamic measure of mobility status.

### METHODS

- 1. Collected minute-level Fitbit EHR data, cognitive, and data, psychosocial data from a cohort of poststroke patients through the Rehabilitation Precision Medicine Center of Excellence
- 2. Performed quality filtering on data, removing infeasible heart rate and step count values.
- 3. Divided each participant's data into 2week windows with valid windows have >=10 days of data and >= 18 hours of data each day. Missing heart rate values were imputed with the window mean.
- 4. Derived several health metrics across heart rate, activity level, and sedentary level domains. Metrics were calculated for each valid window.
- 5. Developed predictive models of clinicbased assessments of mobility, and adverse events.

Heart Rate	Activity	Sedentary
Rolling max	Time in each PA level (low, light, light- moderate, moderate- vigorous)	Total sedentary time
Rolling min	Length of activity bouts	Length of sedentary bouts
Resting HR	Number of bouts	Number of bouts
Sedentary HR		
Resting HR variability		
Return to baseline after activity		

### **FEATURES**







# **Predicting Mobility Status After Stroke Using Fitbit Data**

<sup>1,2,3,4,5,6</sup> Department of Biomedical Engineering, Johns Hopkins University <sup>7,8</sup> Department of Physical Therapy and Rehabilitation, Johns Hopkins Medicine

# Fitbit-derived metrics can be used to determine health status outside of the clinic



## These metrics could be used to predict who is at risk for an adverse event

# Beryl Sawyerr<sup>1</sup>, Michael Liew<sup>2</sup>, Megan Concannon<sup>3</sup>, Lingzhu Shen<sup>4</sup>, Casey Overby Taylor<sup>5</sup>, Joseph Greenstein<sup>6</sup>, Margaret French<sup>7</sup>, Ryan Roemmich<sup>8</sup>



### **RESULTS**

### **Feature Correlations**



### **Clinic Tests**

	Comfortable Walking Speed		Fast Walking Speed	
	RF (Train, Test)	LM	RF	LM
RMSE	0.130,	0.277,	0.278,	0.497,
	0.201	0.455	0.167	0.529
R <sup>2</sup>	0.897,	0.374,	0.844,	0.308,
	0.452	0.455	0.928	0.102

### **Adverse Event Statistical Analysis**

Feature	T-test	LR
Heart rate	0.024	0.003
Sedentary time	0.466	0.062
Activity level	LPA: 0.737 LMPA: 0.300 MVPA: 0.133	LPA: 0.006 LMPA: 0.014 MVPA: 0.543

### **FUTURE WORK**

Although the power of many analyses is limited by small sample sizes, the feature extraction and modeling pipelines developed can be used to offer continuous monitoring of mobility status outside of the clinic, while still offering similar information. Future work will aim to further refine feature selection for modeling and calculate these metrics against a healthy baseline to offer an overall score of mobility. This work could explore time-based further also prediction of when an adverse event is likely to occur.

