Routine Change Detection Using Apple Watches

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Introduction

- Programs to promote brain health have emerged as an important public health initiative
- These programs encourage behavior change, especially in physical activity and cognitive engagement
- Traditional measures for measuring behavior change can be unreliable, inefficient, expensive, or ineffective for short-term change
- Apple Watches, due to their focus on health tracking, may provide a reliable, unobtrusive, cost-effective, and time-efficient way to measure behavior change in free-living conditions

Objectives

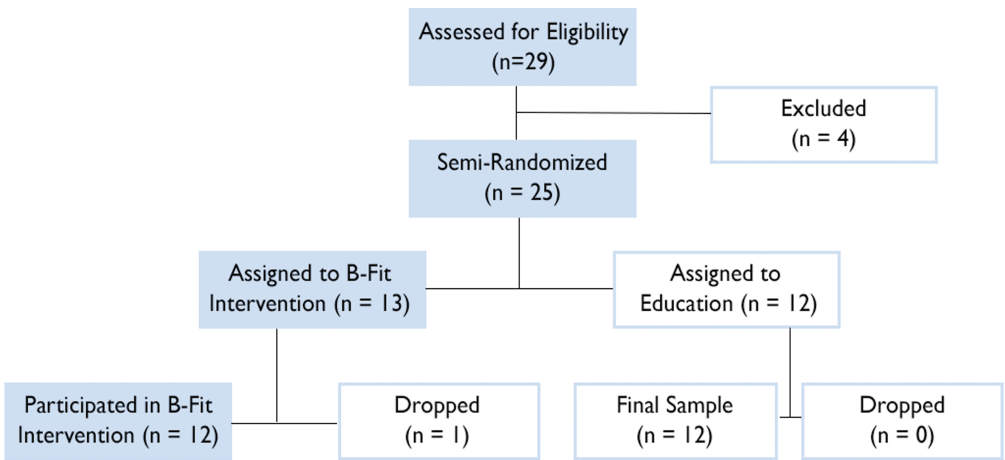
- Determine if Apple Watches can capture changes in routine after starting a behavior change intervention
- Examine patterns of routine behaviors between weeks
- Establish a pipeline for examining change in future patients as part of an ongoing study

Methods

Study Design

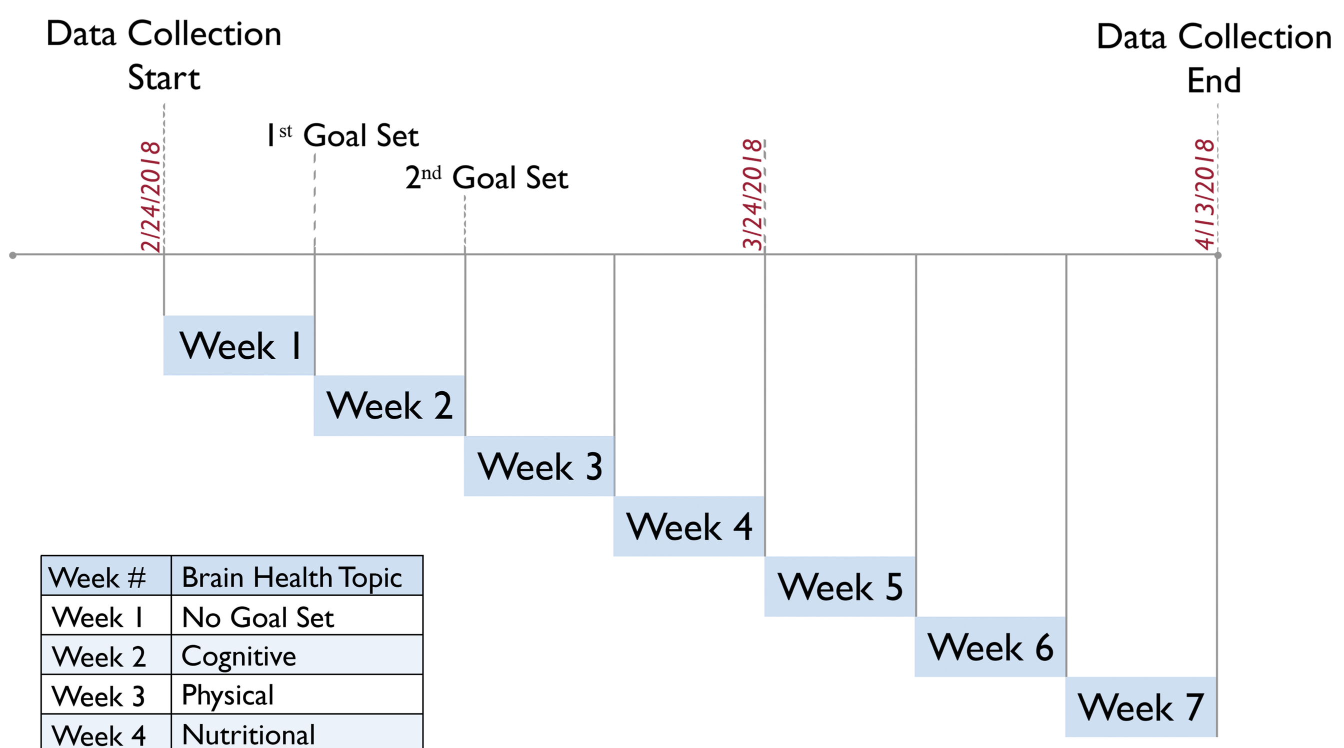
Participants

- Selected from a larger intervention
- Exclusion Criteria: a known medical, neurological, or psychiatric cause of cognitive disfunction



B-Fit Intervention

- The intervention lasted 7 weeks, with a 2-hour long weekly meeting
- Participants were provided psychoeducation on both brain health, and skills for behavior health change
- Individuals identified a daily goal based on a week's brain health topic
- All weekly goals are cumulative (ex: Week 1 goal is continued through Week 7)



Week #	Brain Health Topic
Week 1	No Goal Set
Week 2	Cognitive
Week 3	Physical
Week 4	Nutritional
Week 5	Social
Week 6	Sleep
Week 7	Compensatory

Methods

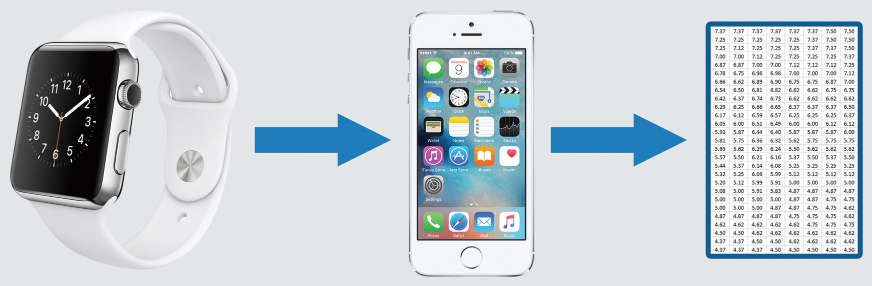
Hardware and Software

Participant Use of Apple Watches
- Each participant given two watches: one for daytime use, one for nighttime use

Apple Watch Sensors
- Contain accelerometers, gyroscopes, altimeters, and GPS
- Transmits data via Wi-Fi and Bluetooth

iOS Application
- Receives data from the Apple Watch,
- Exports the data to WSU hosted server

Data Parsing
- Watches collect data in 5 second-long intervals, followed by a 5 minute pause
  - This is done to preserve battery life of both the phone and watch



Apple Watch Inclusion
- Apple Watches selected due to their availability as consumer items, as well as their mobility in comparison to stationary sensor types

Data Processing

Labeling Data

- Features extracted from raw Apple Watch data
  - Including, but not limited to: Mean, min, max, sum, median, zero crossings
- Random Forest Classifier trained with separate, pre-labeled Activity Learning files
- Intervention participant data labeled using trained RFC model

Feature Extraction

- Probability Distribution Table is calculated for each hour of a patient's intervention

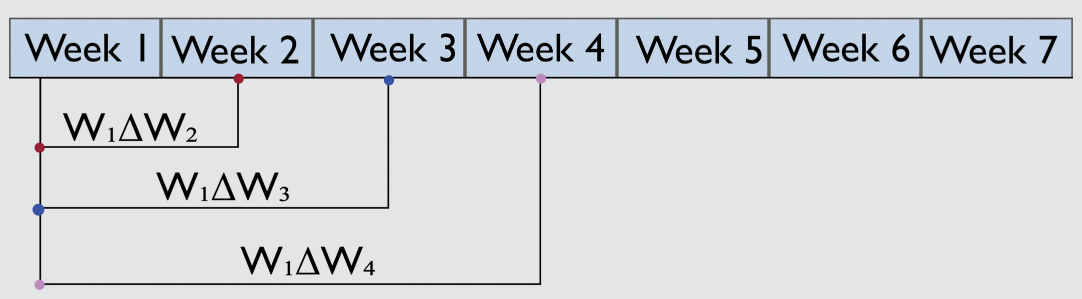
	chores	eat	errands	exercise	hobby	hygiene	school	sleep	travel	work
10:00:00 AM	0	0.083	0	0	0.16	0	0	0	0	0.75
11:00:00 AM	0	0.09	0	0	0.45	0	0	0	0	0.45
12:00:00 PM	0	0.083	0	0	0.66	0	0	0	0	0.25
1:00:00 PM	0	0	0.083	0	0.5	0	0	0	0.42	0

Missing Data & Imputation

- First day of data collection removed due to incompleteness
- Missing data imputed via normalized average of other days within window
- Data was sectioned into seven week-long (seven day) windows, corresponding to the seven weeks of the intervention
- Missing days (at beginning of data collection) imputed via technique mentioned above

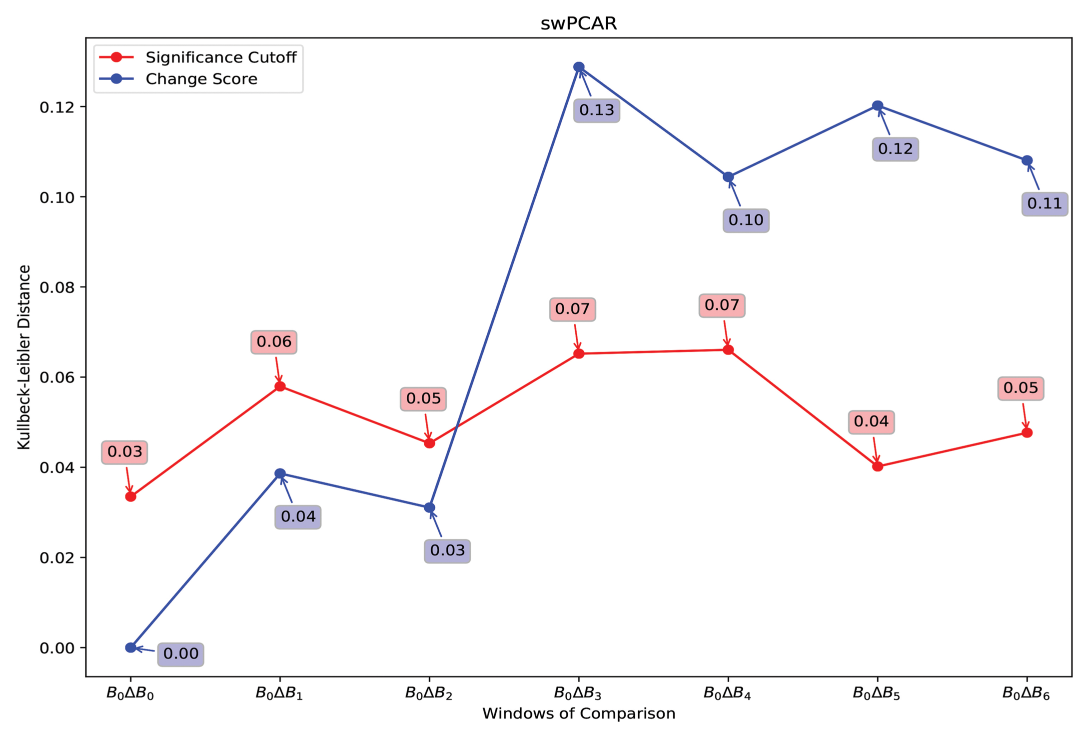
Data Analysis: Physical Activity Change Detection [1]

- PACD used to analyze changes for each participant with Apple Watch data
  - Modified to accept weeks, as opposed to days
- 2 distinct change score metrics are used: swPCAR (permutation based change detection in activity routine algorithms), and VC (Virtual Classifier)
- Week 1, where each participant did not set a goal, served as a "baseline" window, to which all other weeks are compared

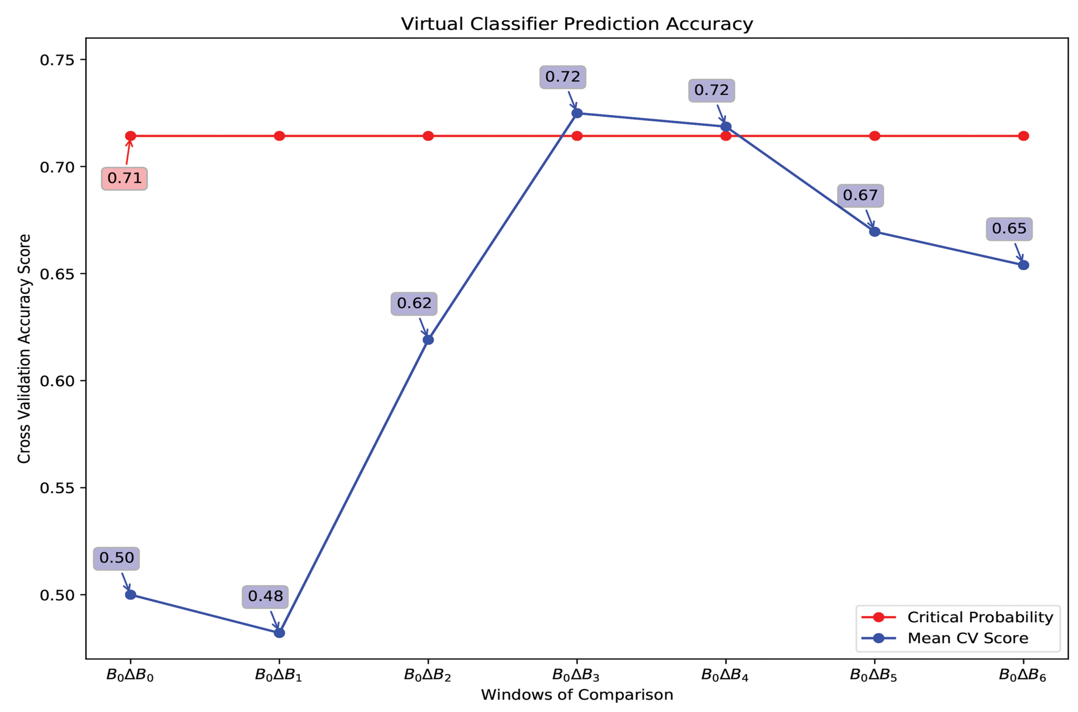


Results

Following results are PACD Algorithms performed on single patient's watch data



Comparisons made after week 3 have a change score higher than the significance threshhold, meaning there is significant change between those weeks and week 1



Comparisons involving weeks 4 and 5 have a change score higher than the significance threshhold, meaning there is significant change between those weeks and week 1

Discussion

- The change scores when comparing weeks 2 and 3 to week 1 are surprisingly low, considering it is the first occurence of any behavioral change by the participant
- The highest change scores in both swPCAR and VC are found when comparing weeks 4 and 5 to week 1
- In weeks 4 and 5, the participant spent, on average, 3.6% less time working, and 4.4% more time on hobbies, which may explain the high change scores in that timeframe
- The disparity between swPCAR and VC may be due, in part, to different variable weights (VC placed the highest value on time eating, while swPCAR placed the highest value on time classified as work and hobby)

Future Work

- Perform Routine Change Detection on the rest of the original B-Fit dataset (n=11)
- Perform Routine Change Detection on data accumulated in further rounds of data collection
- Further research methods for data cleaning and imputation

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References

[1] Sprint, G., Cook, D., Fritz, R., and Schmitter-Edgecomb, M. (2016). Using Smart Homes to Detect and Analyze Health Events. IEEE Computer , 49(11), 29-37. doi:10.1109/MC.2016.338