

Detecting Health and Behavior Change by Analyzing Smart Home Sensor Data

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Association for Computing Machinery



Health and Behavior Monitoring

Age, injury, or health-related impairments can impact health Benefits of health and behavior monitoring

- Health insights
- Longitudinal tracking
- Aging in place

Preferably monitor 24/7 Objective data collection

CLINICAL STUDIES SUPPORT A RELATIONSHIP BETWEEN DAILY BEHAVIOR AND COGNITIVE AND PHYSICAL HEALTH





Technologies for Behavior Monitoring

Ambient sensors (installed in the environment)





Wearable sensors (inertial, vital sign, etc.)



Smartphone/tablet apps





SELF-PERCEPTION OF BEHAVIOR OFTEN DOES NOT ALIGN WITH DIRECT MEASUREMENT



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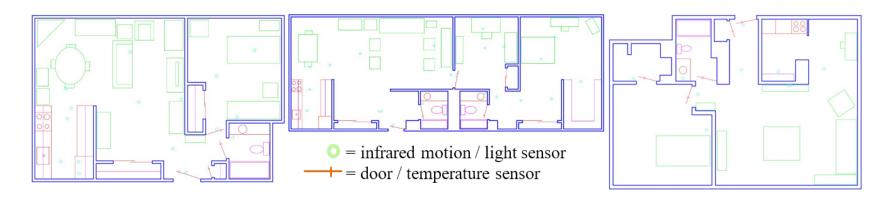


Smart Home Environments

Ambient sensors installed in the home

- Motion, door, temperature, etc.
- Fire event when state changes

WE COLLECTED DATA FROM SMART HOMES WITH OLDER ADULT RESIDENTS







Activity Recognition (AR)

CASAS-AR algorithm assigns activity labels

- Machine learning
- Cook, eat/drink, relax, sleep, enter/leave home, etc.

Timestamp/Identifier/Message	Sensor Location	Activity
2014-06-15 03:38:28.094897 M009 ON	BedroomMotion	Sleep
2014-06-15 03:38:29.213955 M009 OFF	BedroomMotion	Sleep
2014-06-15 03:38:17.814393 M015 ON	BathroomMotion	Bed-Toilet
2014-06-15 03:38:58.584179 M015 OFF	BathroomMotion	Bed-Toilet
2014-06-15 03:39:17.814393 M009 ON	BedroomMotion	Sleep





Tracking Behavior Changes

Analyze AR-labeled data to track resident behavior Behavior Change Detection (BCD) framework

- Input: AR-labeled data
- Output: Quantification of change
- Output: Explanation of change

Focus on indicators of health events





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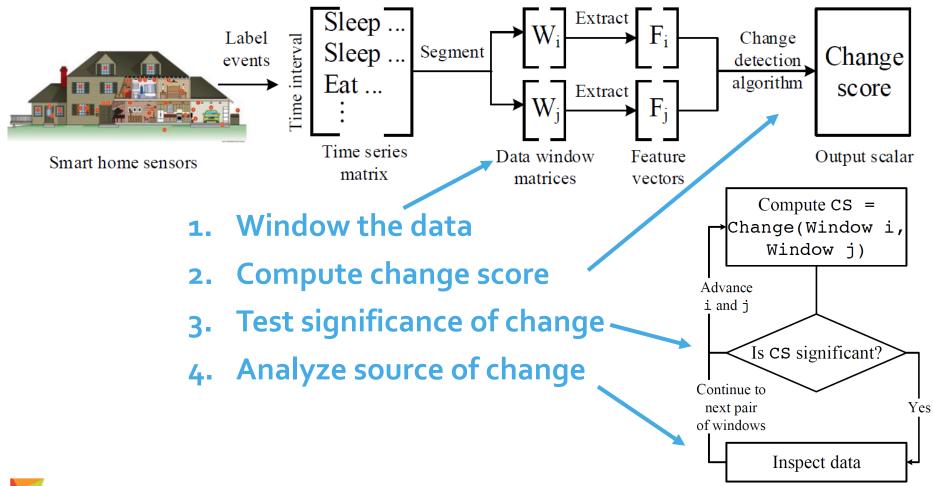
Behavior Change Detection (BCD) Framework



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BCD Framework





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Change Detection Algorithm

A change detection algorithm

- Accepts two windows of data
- Quantifies the change
- double changeScore = computeChange(Window_i, Window_j)
 Different algorithms detect different change
- Virtual Classifier [Hido et al., 2008]
- RuLSIF [Liu et al, 2013]
- sw-PCAR [Sprint et al., 2016]

Focus on Virtual Classifier

WE INVESTIGATED 3 DIFFERENT CHANGE SCORE ALGORITHMS









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Case Studies

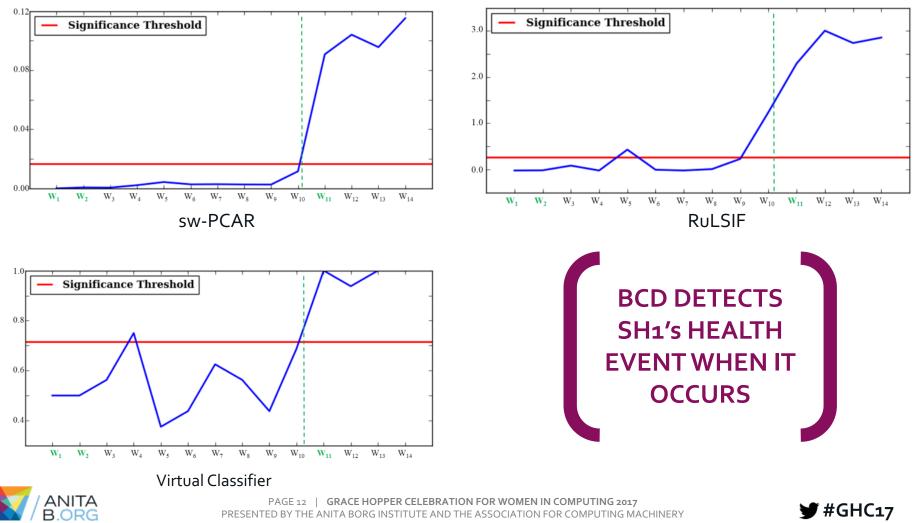
Smart home residents with health events

- SH1: 86 year old female
 - Diagnosed with lung cancer
 - Started radiation treatment during week 10
- SH2: 91 year old female
 - Diagnosed with insomnia during week 11

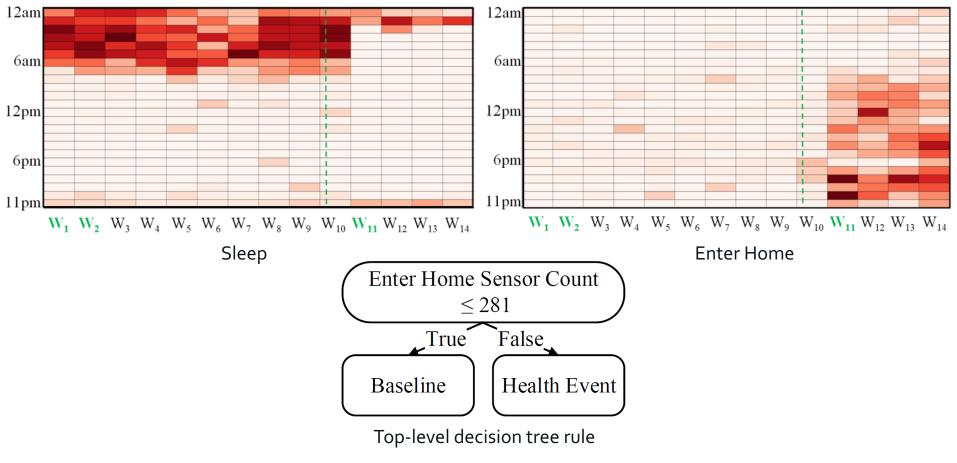




SH1 Health Event Results (started radiation treatment during week 10)



SH1 Explanation of Change (started radiation treatment during week 10)

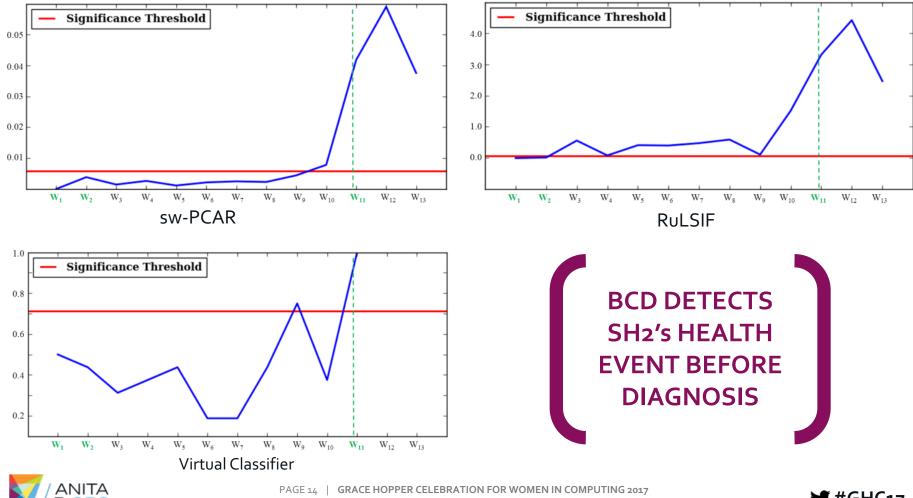




PAGE 13 | GRACE HOPPER CELEBRATION FOR WOMEN IN COMPUTING 2017 PRESENTED BY THE ANITA BORG INSTITUTE AND THE ASSOCIATION FOR COMPUTING MACHINERY



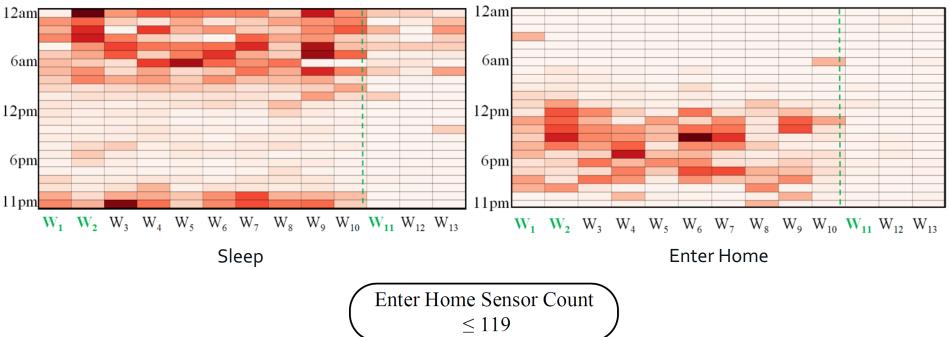
SH2 Health Event Results (diagnosed with insomnia during week 11)

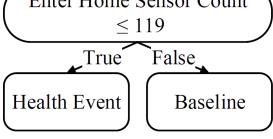


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SH2 Explanation of Change (diagnosed with insomnia during week 11)





Top-level decision tree rule



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What's Next?

Impact

- Relationship between health and behavior
 - Over time
- Aging in place
- Motivation toward health goals

Future Work

- Different health events
- Vital sign data
- Interface caregivers

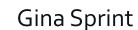






Thank You!





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Acknowledgments

- Co-authors: Diane Cook, Shelly Fritz, Maureen Schmitter-Edgecombe
- WSU CASAS-AR algorithm: [NC Krishnan and Diane Cook, 2014]

Related Publications

- G. Sprint, D. Cook, R. Fritz, and M. Schmitter-Edgecombe. <u>Using Smart Homes to</u> <u>Detect and Analyze Health Events</u>. IEEE Computer, 2016.
- G. Sprint and D. Cook. <u>Unsupervised Detection and Analysis of Changes in Everyday</u> <u>Physical Activity Data</u>. Journal of Biomedical Informatics, 2016.
- G. Sprint, D. Cook, R. Fritz, and M. Schmitter-Edgecombe. <u>Detecting Health</u> <u>Changes by Analyzing Smart Home Sensor Data</u>. IEEE SmartComp Conference, 2016







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Thank you

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Virtual Classifier

Train a binary decision tree classifier

- Extract features
- Label feature vectors in *Window_i* as positive class
- Label features vectors in *Window_i* as negative class
- Average K-fold cross validation accuracy

Investigate source of change

- Accuracy significant?
- Investigate decision tree

WE TRAIN DECISION TREES TO LEARN THE DIFFERENCES BETWEEN TWO WINDOWS



