Collecting High-frequency Mobile Sensor Data for Long-lasting Research Utility

Santosh Kumar

Director, MD2K Center of Excellence

Professor & Lillian and Morrie Moss Chair of Excellence

Department of Computer Science, University of Memphis

NSF

NIH Big Data to Knowledge (BD2K)

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Open mHealth

Computer Science

UCSF University of California San Francisco
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Medicine

MD2K
Center of Excellence for Mobile Sensor Data-to-Knowledge

Behavioral Health

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UNIVERSITY OF MICHIGAN
NORTHWESTERN UNIVERSITY
RICE
UC San Diego

Electrical Engineering

OHIO STATE
UCLA

MD2K Multidisciplinary Team – 20 investigators

Data Science Research

- Santosh Kumar, ***Memphis*** (**PI**)
- Gregory Abowd, Polo Chau, and Jim Rehg, ***Georgia Tech***
- Emre Ertin, ***Ohio State***
- Deborah Estrin, ***Cornell Tech***
- Tyson Condie, Mani Srivastava, ***UCLA***
- Deepak Ganesan, Ben Marlin, ***UMass***
- Susan Murphy, ***Harvard***

Health Research

- William Abraham, ***Ohio State***
- Inbal Nahum-Shani, ***Michigan***
- Bonnie Spring, ***Northwestern***
- Cho Lam, Dave Wetter, ***Utah***
- Vivek Shetty, ***UCLA***
- Ida Sim, ***UC San Francisco***
- Jaqueline Kerr, ***UC San Diego***
- Clay Marsh, ***West Virginia***

Memphis-based headquarter hosts a team of 10 grad students, a postdoc, 3 software engineers, and 6 staff members

Measuring Exposures, Behaviors, and Outcomes

Mobile Sensors

Smartwatch

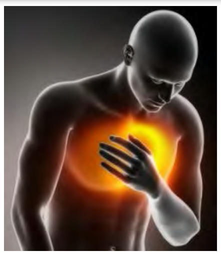
Chestbands

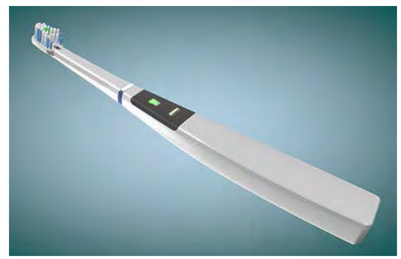
Smart Eyeglasses

Exposures

Behaviors

Outcomes





MD2K Center of Excellence for Mobile Sensor Data-to-Knowledge

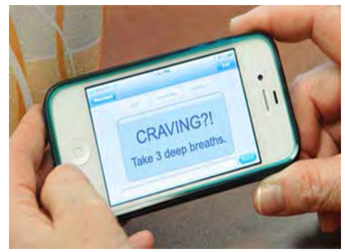
Advancing biomedical discovery and improving health through mobile sensor big data

Cornell Tech ♦ Georgia Tech ♦ U. Memphis ♦ Northwestern ♦ Ohio State ♦ Open mHealth
Rice ♦ UCLA ♦ UC San Diego ♦ UC San Francisco ♦ UMass Amherst ♦ U. Michigan ♦ WVU

MD2K Applications – Smoking Cessation & CHF

Detect → **Predict** → **Adapt**



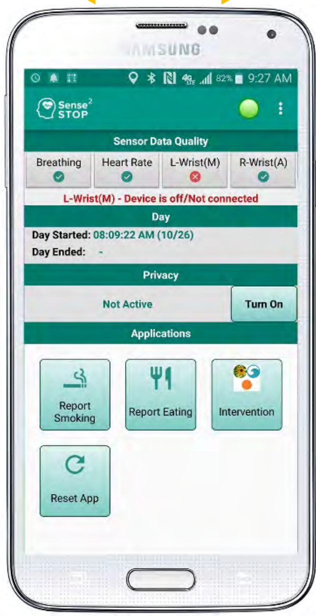






Mobile Sensor Data Sources in MD2K

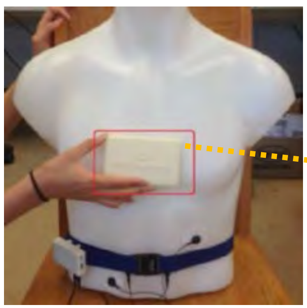
AutoSense sensors: ECG, respiration, accelerometers

Microsoft Band: accelerometers, gyroscopes, HR



Smartphone sensors: GPS, accelerometers, self-report

MotionSense HRV: accelerometers, gyroscopes, PPG



EasySense (contactless) sensors: heart motion, lung motion, lung fluid level

Smart toothbrush: brushing, Pressure

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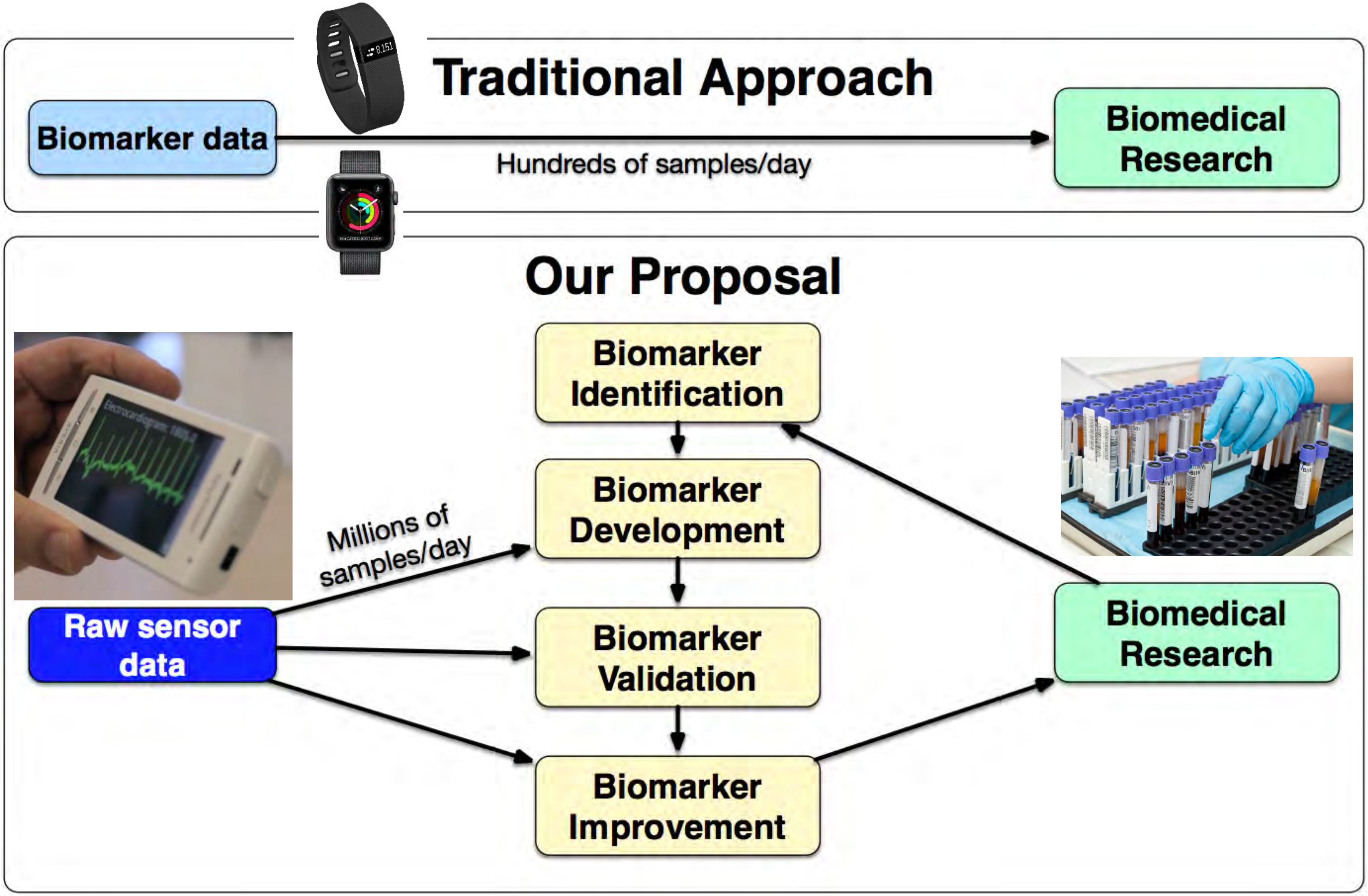
Utility of Collecting High-frequency Sensor Data

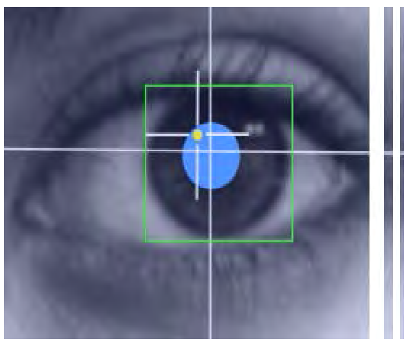
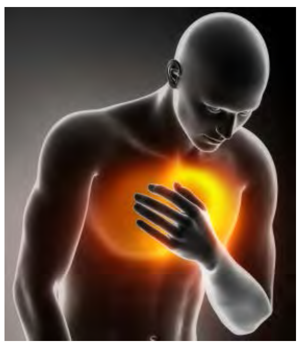


mHealth Biomarkers Developed in MD2K







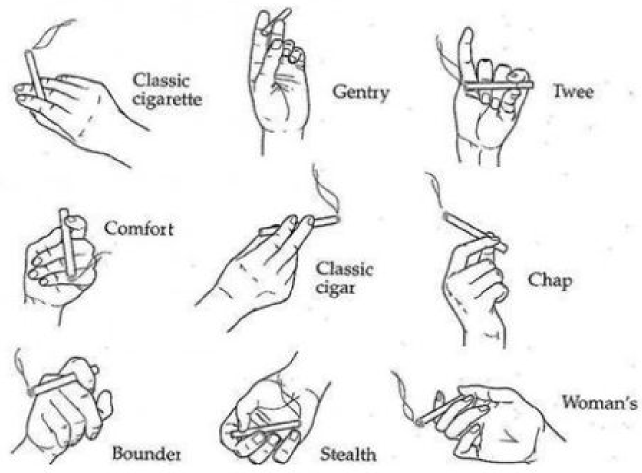

Detecting First Lapses in Smoking Cessation

Saleheen, et. al., ACM UbiComp 2015

Modeling Challenges

1. **Ephemeral (very short duration)**
   - **3~4 sec** for each puff
   - 10,000 breaths in 10 hours
   - 2,000 hand to mouth gestures
   - But, only 6~7 positive instances
   - **Need high recall & low false alarm**
2. **Numerous confounders**
   - Eating, drinking, yawning

Wide person & situation variability



https://www.pinterest.com/pin/526710118890712075/

Main Results

- **Applied on smoking cessation data from 61 smokers**
- **Detected 28 (out of 33) first lapses**
- **False alarm rate of 1/6 per day**

Limitations

- **Can't detect if sensor not worn**
- **Can't detect if data quality is poor**
- **Needs adaptation for e-cigarettes**
- **Difficult to validate temporal accuracy of smoking detection**

Sensors-to-Markers-to-Interventions:
The Case of Sensor-Triggered Stress Intervention

SENSE

[Ertin, et. al., ACM SenSys'11]

ECG, Respiration — 4M samples/day → cStress

Accelerometer — 1M samples/day → Activity

- High data rate streaming
- Long battery life
- High data yield
- Real-time data quality screening

ANALYZE

[Hovsepian, et. al., ACM UbiComp'15]

cStress — 9K samples/day → Time series pattern mining

Activity — 4K samples/day → Time series pattern mining

- Personalized machine learning models
- Biomarkers of health, behavior, and environment
- Validated in lab and field

ACT

[Sarker, et. al., ACM CHI'16]

Time series pattern mining → Stress Episode Detection → Intervention Trigger

1-2 Interventions/day

- Detect trend in noisy and rapidly varying time series
- Robust to confounders and data losses
- Adapt intervention prompts to current context (e.g., driving)

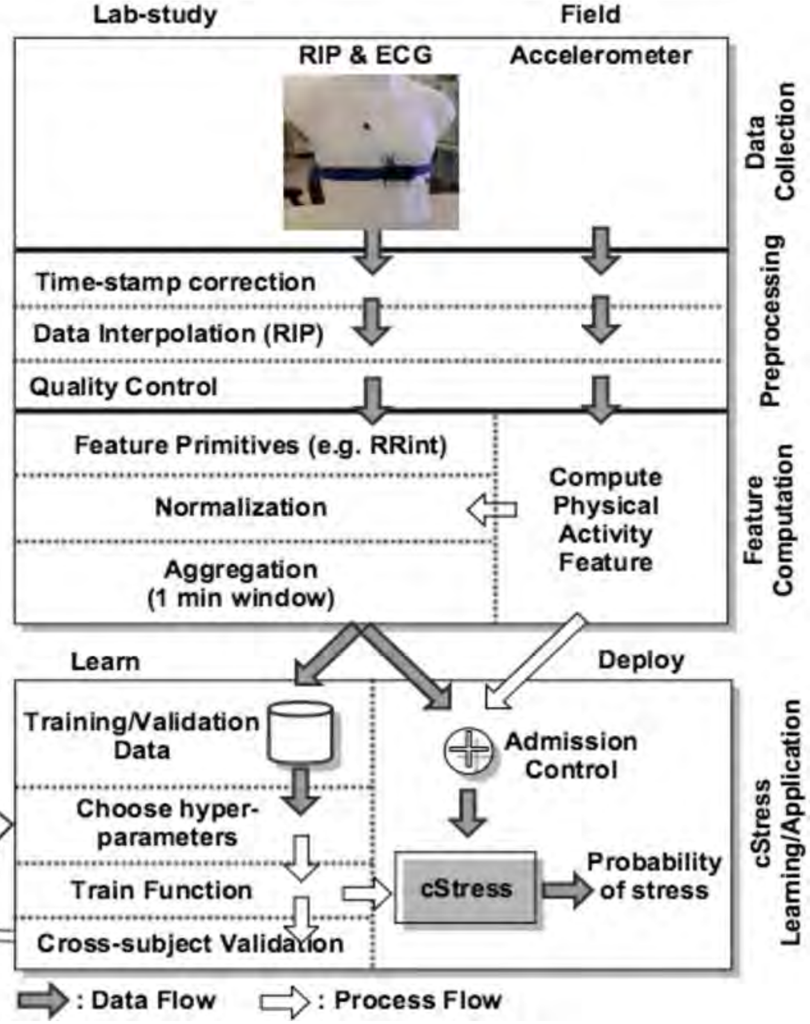
cStress: Continuous Measure of Stress

Hovsepian, et. al., ACM UbiComp 2015

1. A model to convert ECG & respiration sensor data into a continuous measure of stress
- input: vector of all one-minute ECG + RIP statistical/aggregate features
- output: “stress”/“non-stress” label
- alternative output: probability of “stress”

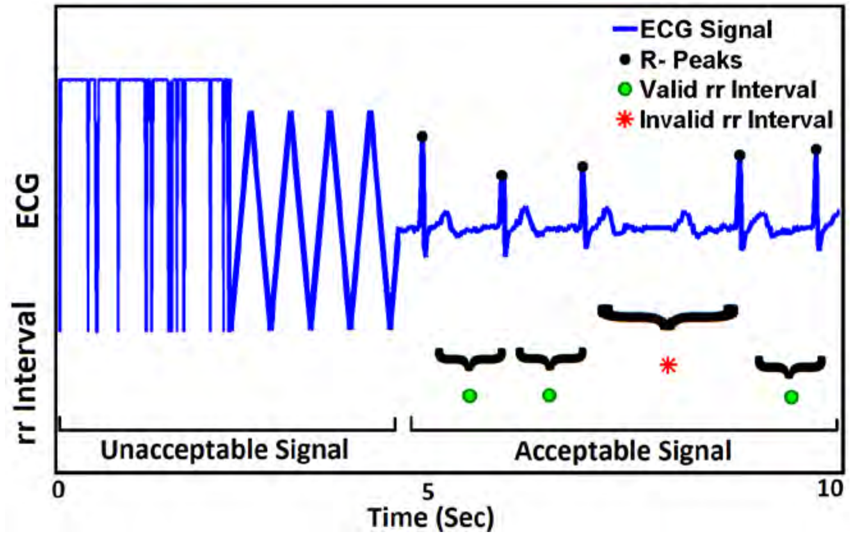
2. Learned with Support Vector Machines (SVM)
- Careful handling of sensor data
- Parameters tuned for optimizing F1 score
- Cross-subject validation for generalizability
- Data loss (0.27 hr/day)

3. Validated on independent data sets
- Against lab stress protocol for lab data
- Against self-report for field data



Feature Computation from ECG

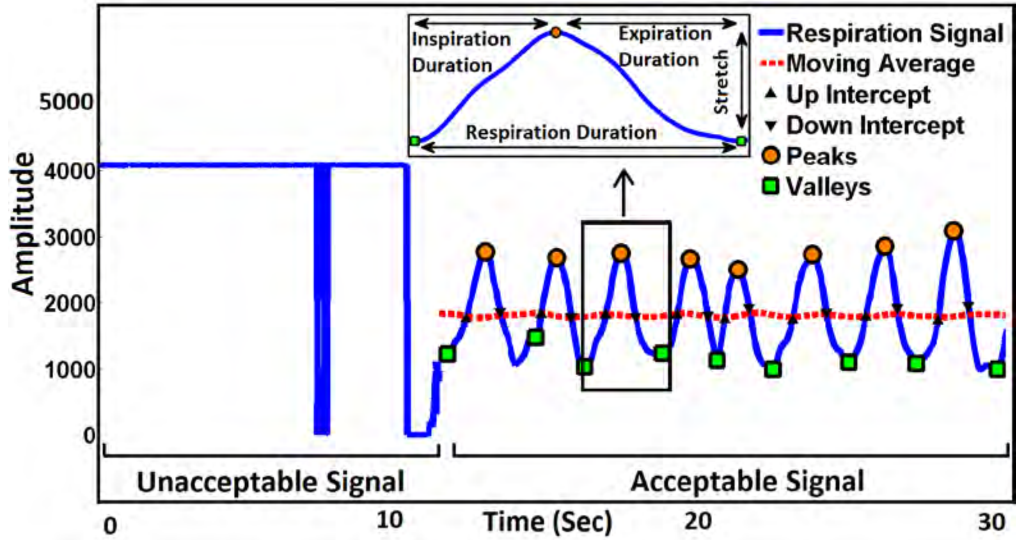
- Screen for data quality
  - Morphology, saturation, etc.
- Find R peaks
  - Pan and Tompkin's algorithm
- Compute R-R interval
- Detect/remove noisy R-R intervals
- Normalize R-R intervals
  - Use "winsorized" (capped) mean/stdev estimates
  - Filter out activity affected data
- Compute one-minute statistics of R-R intervals



HRV	variance, quartile deviation, low frequency energy (0.1–0.2Hz), medium frequency energy (0.2–0.3Hz), high frequency energy (0.3–0.4Hz), low:high frequency energy ratio
non-HRV	mean, median, 80th percentile, 20th percentile, heart-rate

Feature Computation from Respiration

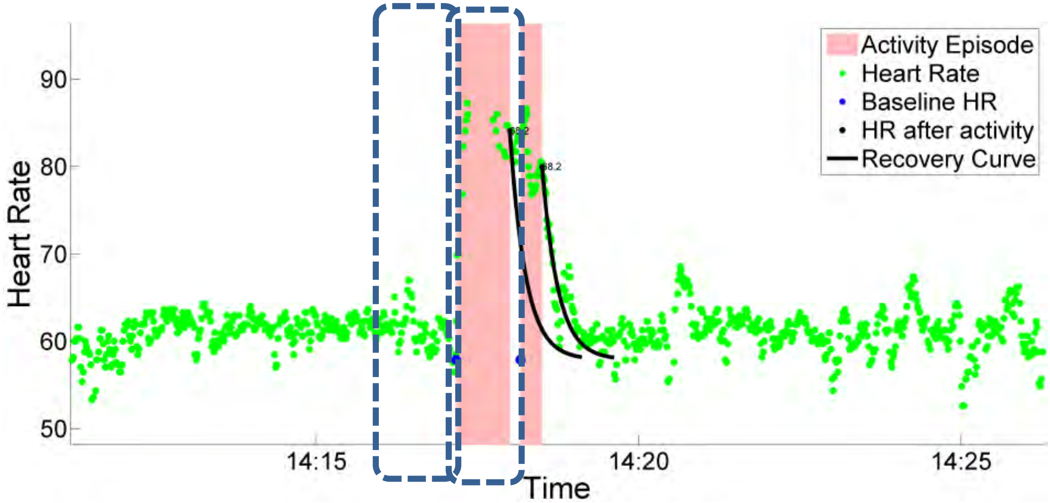
- Screen for data quality
  - Morphology, loosening
- Locate respiration cycles
- Detect/remove invalid cycles
  - **Amplitude:** > 20% of mean
  - **Duration:** 0.9 - 12.5 sec
- Compute base features
- Normalize base features
  - As in ECG
- Compute one-minute statistics of base-features



Base Features	Aggregations
inspiration duration, expiration duration, respiration duration, I:E duration ratio, stretch, respiratory sinus arrhythmia (RSA)[1]	mean, median, 80th percentile, quartile deviation
breath-rate[2], inspiration minute volume[2]	

Minimizing the Data Loss due to Physical Activity

Sarker, et. al., ACM CHI 2016



Heart-rate exponential recovery

$$HRR = HR_{Rest} + (HR_{Peak} - HR_{Rest})e^{-\frac{t-t_0}{\tau}}$$

[Freeman, PCD 2006]

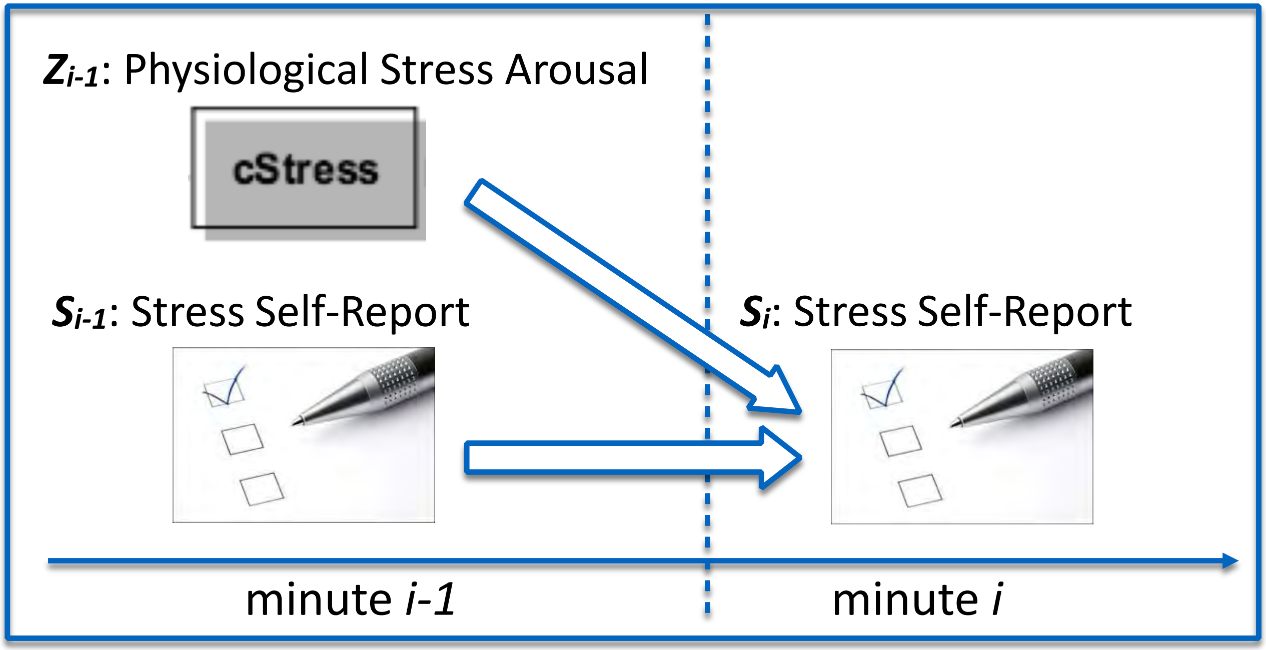
Data Loss due to Physical Activity

Recovered: 27.6%

	Discard 2 minutes	Proposed Method
Activity	22.7%	22.7%
Residue	**35.0%**	**7.4%**
Total	57.7%	30.1%

Training & Validation Methods

- **Lab:** Model trained using lap protocol
  - Public speaking, mental arithmetic, and cold pressor sessions
- **Field:** A Bayesian Network model to map minute-level outputs from cStress to self-reports
  - Random prompts (5-15 per day)



		S_i	
S_{i-1}	Z_{i-1}	**1**	**0**
1	**1**	1	0
1	**0**	α	$1-\alpha$
0	**1**	β	$1-\beta$
0	**0**	0	1

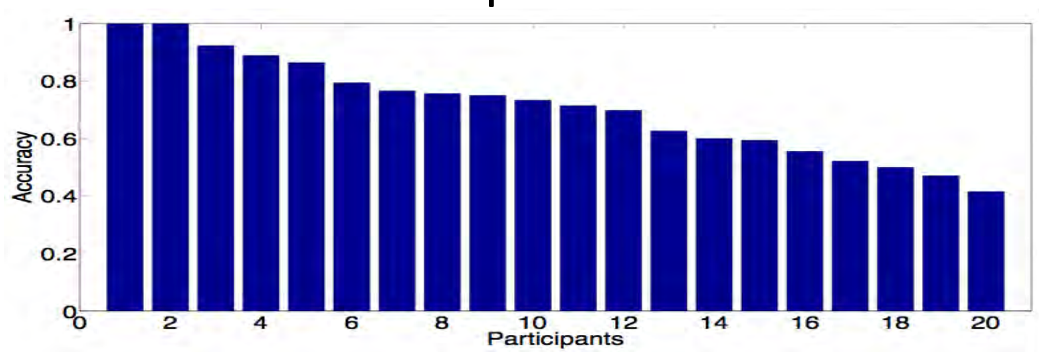
Validation in Independent Lab and Field Data

- **Lab Validation:** Cross-subject validation with *n*=21, 1600 minutes of lab data
- Stress sessions consist of public speaking, mental arithmetic, cold pressor

			Accuracy				Optimal hyper-parameters		
Feature Set	F1	AUC	Hit-rate	TPR	FPR	C. Kappa	*C*	γ	*bias*
All	0.81	0.96	0.93	0.84	0.05	0.77	90.5097	0.000345267	0.339329
ECG	0.78	0.95	0.92	0.72	0.05	0.73	2	0.00552427	0.340407
HRV	0.56	0.78	0.84	0.55	0.1	0.46	724.077	0.0220971	0.250926
RIP	0.75	0.93	0.90	0.83	0.09	0.69	1448.15	0.000488281	0.308312

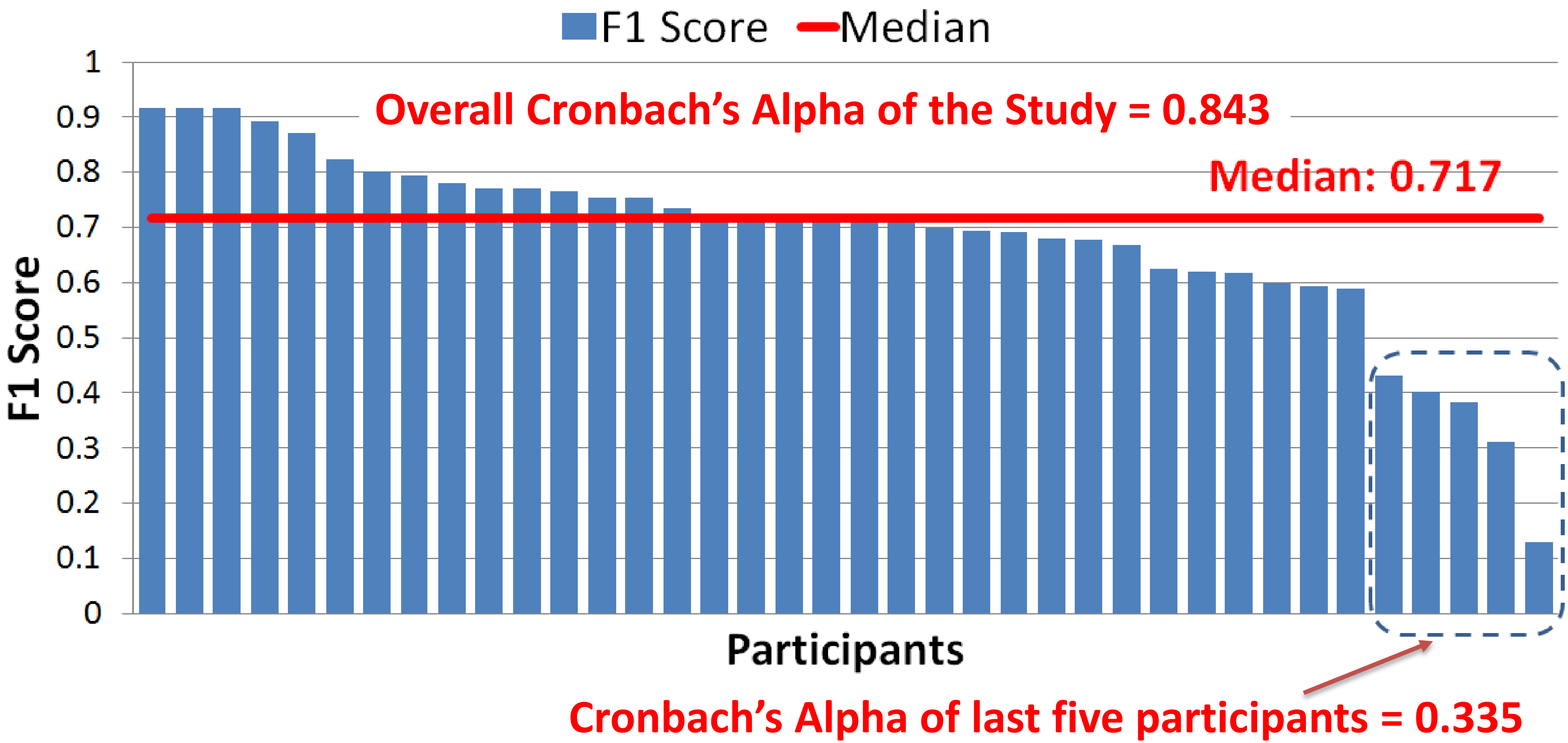
- **Field Validation:** 1601 self-report EMA from *n*=23 over 7 days in the field
- Bayesian network model to map cStress onto self-reported stress data

	train	*field*
Median F1	0.75	0.71
Median AUC	0.85	0.60
Median Accuracy	0.9	0.72



Validation of cStress on 38 Drug Users Dataset

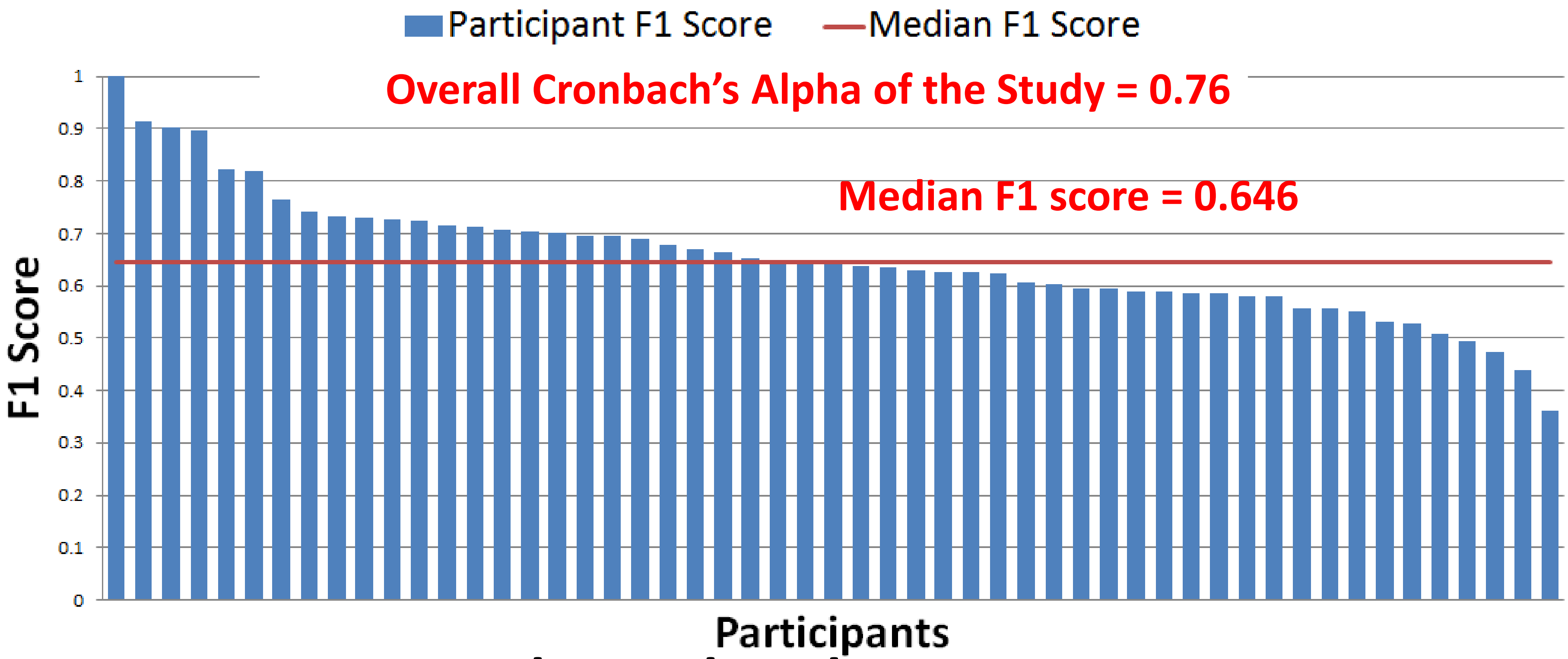
4 weeks of sensor wearing by polydrug users at NIDA IRP (PI: Dr. Kenzie Preston)



[Sarker, et. al., ACH CHI'16]

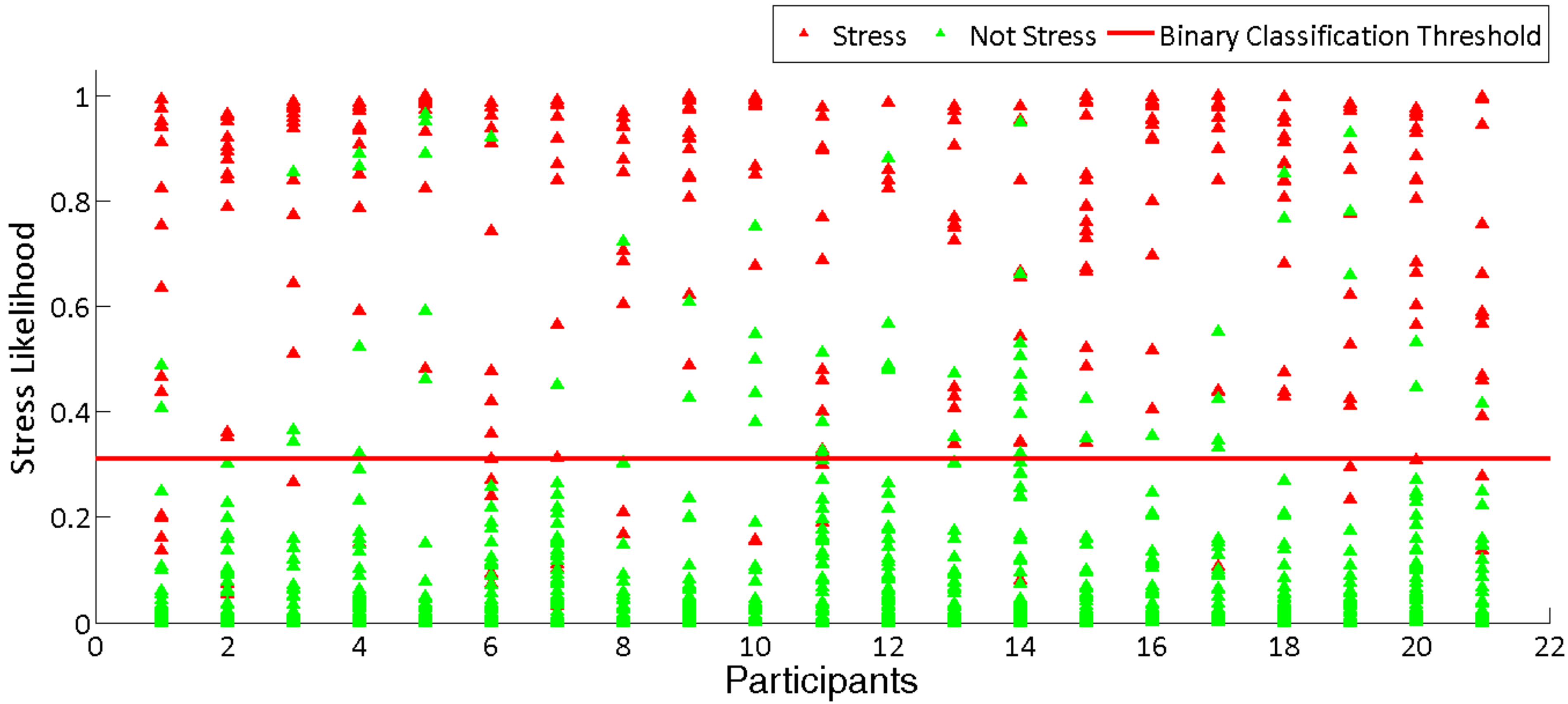
Validation of cStress on Smoking Data

1 day pre-quit and 3 days post-quit sensor wearing by 61 newly abstinent smokers at UMN (PI: Dr. Mustafa al'Absi)



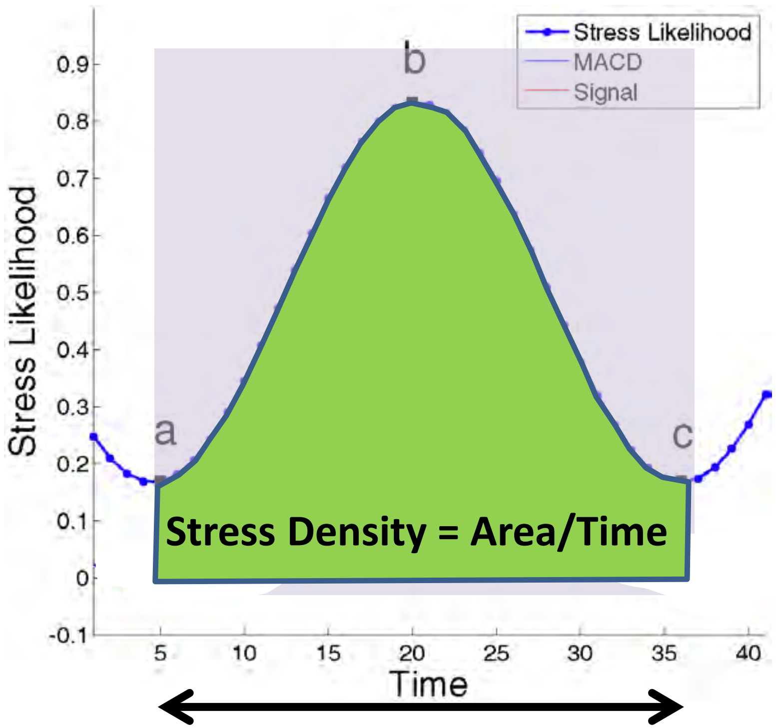
- **Lower F1 score than other datasets**
  - Imputed missing data, but using simple carry-forward
  - Lower consistency of self-reports (0.76 vs. 0.843)

Stress Likelihood Timeseries

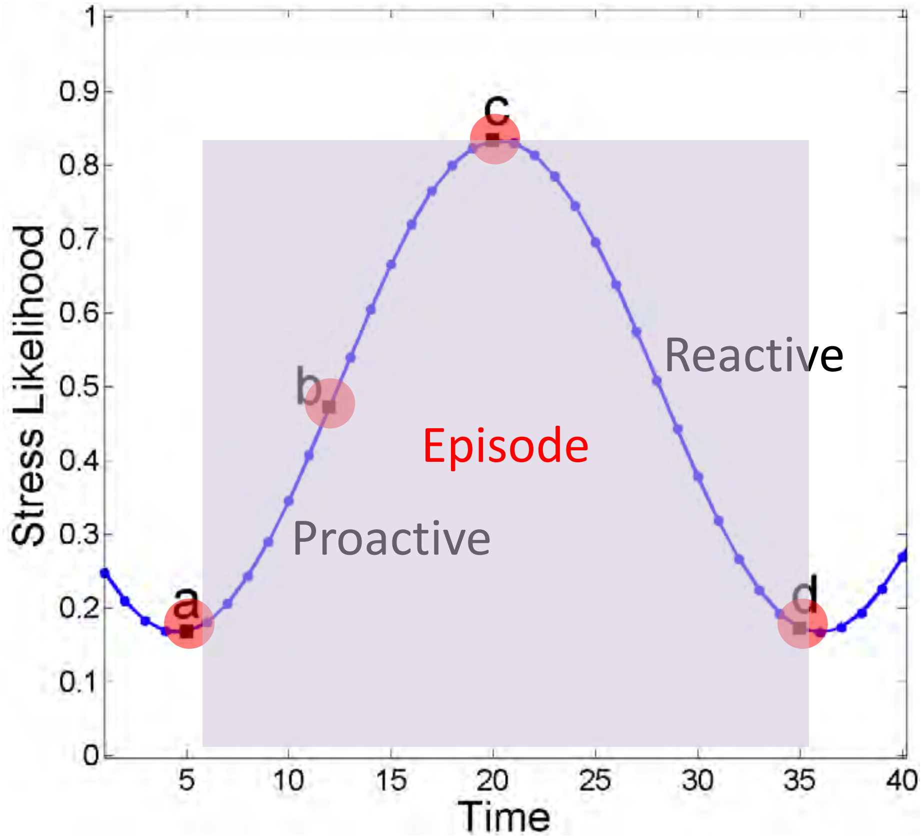


Mining Stress Episodes in cStress Time Series

Stress Likelihood → Stress Density

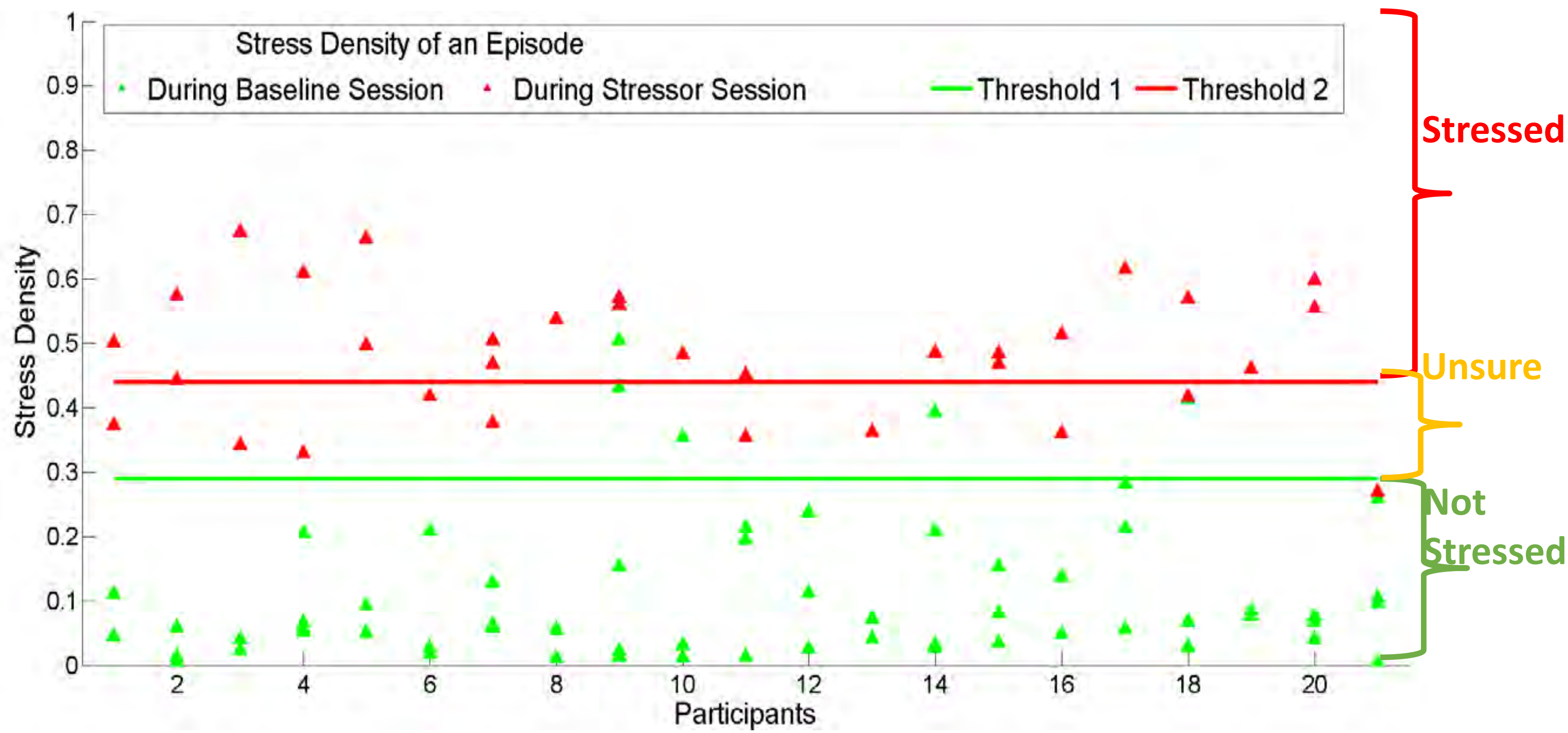


Options for Intervention Timing

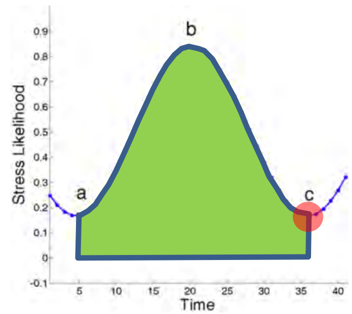


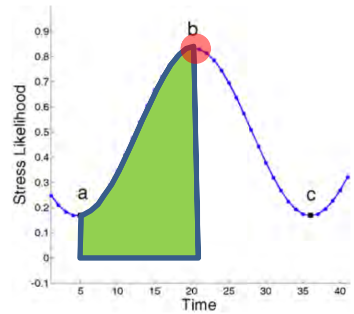
Generating Intervention Triggers - Model Training

Moving from a Single Threshold to Dual Thresholds To Optimize Confidence



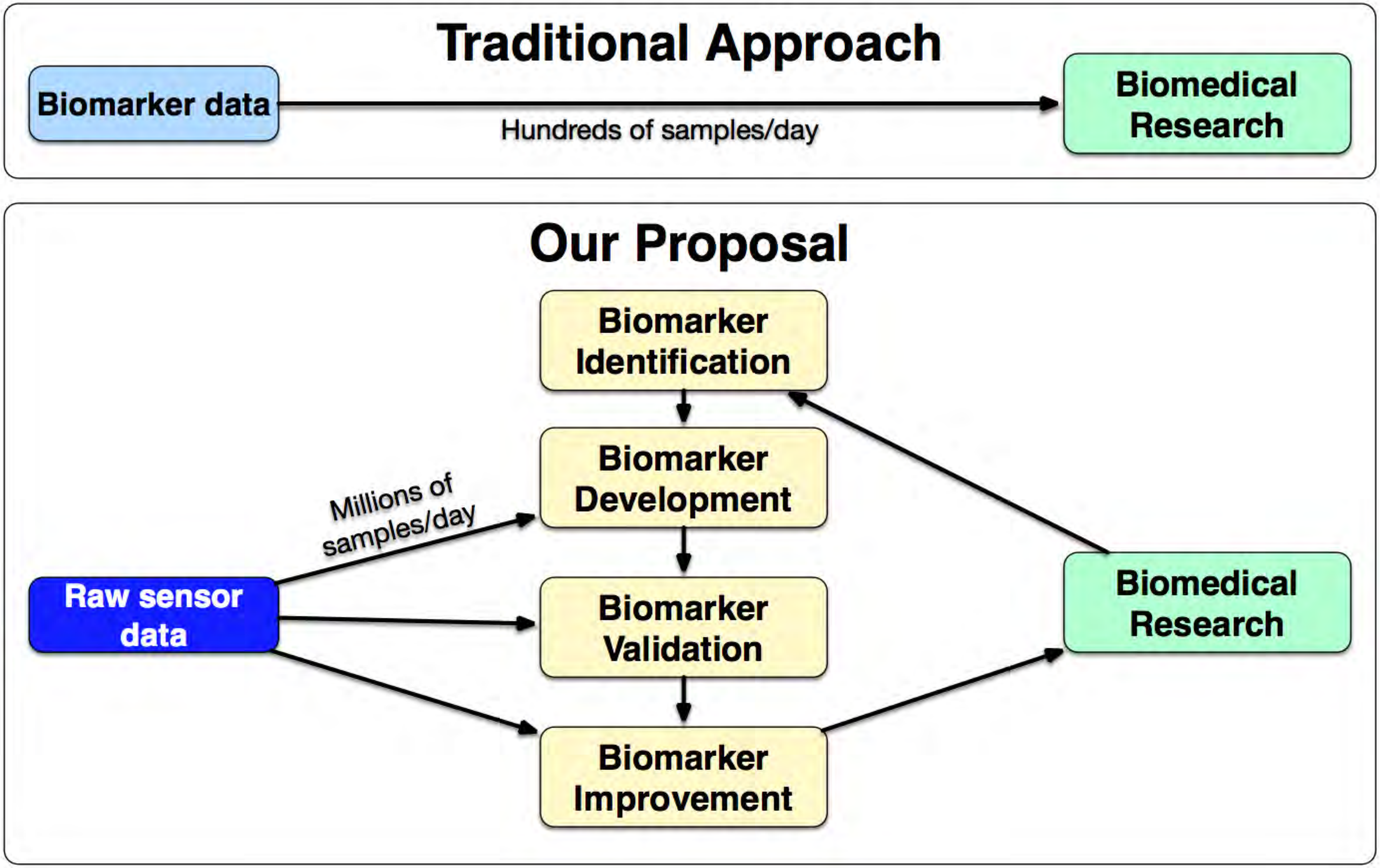
Thresholds for Reactive Stress Intervention



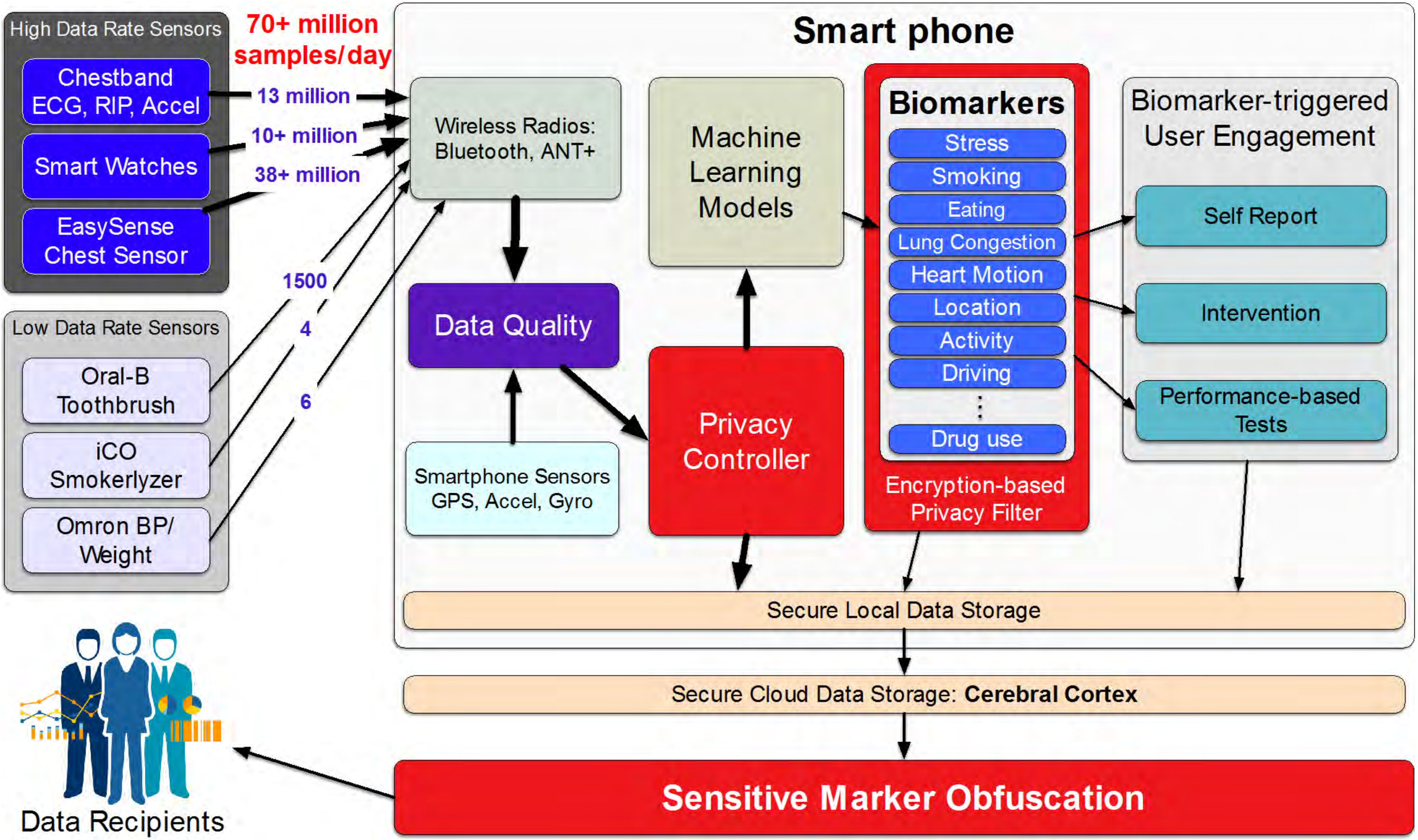


		Precision and Recall			Precision and Recall	
		95%	90%	85%	90%	85%
Lab Study (Stress Density)	Threshold 1	0.29	0.29	0.29	0.36	0.36
	Threshold 2	0.44	0.42	0.29	0.33	0.36
Field Study (per day)	Not-stress	28.3	28.3	28.3	28.9	29.8
	Unsure	2.7	2.5	0	0.9	0
	Stress	1.5	1.7	4.2	5.1	5.1

Utility of Collecting High-frequency Sensor Data



MD2K Mobile Software Platform (open-source)



Key Capabilities of mCerebrum

1. Support for high-frequency streaming data
   - 800+ Hz for 70 million samples per day
2. Connectivity to diverse sensors and radio
   - ANT, Bluetooth, Bluetooth Low Energy (BLE), etc.
3. Continuous data collection and real-time data quality monitoring
4. Real-time computation of biomarkers
   - Stress, smoking, driving, activity, etc.
5. Biomarker-triggered notification/intervention

Field Studies Using MD2K Software

Study	Users	Person-Days	Samples (Billions)
Northwestern (Smoking and Eating)	225	3,150	136
Rice (Smoking)	300	4,200	182
Utah (Smoking)	300	4,200	182
Vermont (Smoking and fMRI)	90	1,260	55
Moffitt (Smoking and Stress)	24	336	15
Ohio State (Heart Failure)	225	6,750	224
UCLA (Oral Health)	162	29,160	968
Johns Hopkins (Cocaine Use)	25	350	18
Dartmouth (Behavior Change)	100	1400	58
Minnesota (Workplace Performance)	800	56,000	2,891
Total	**2,251**	**106,806**	**4,729**

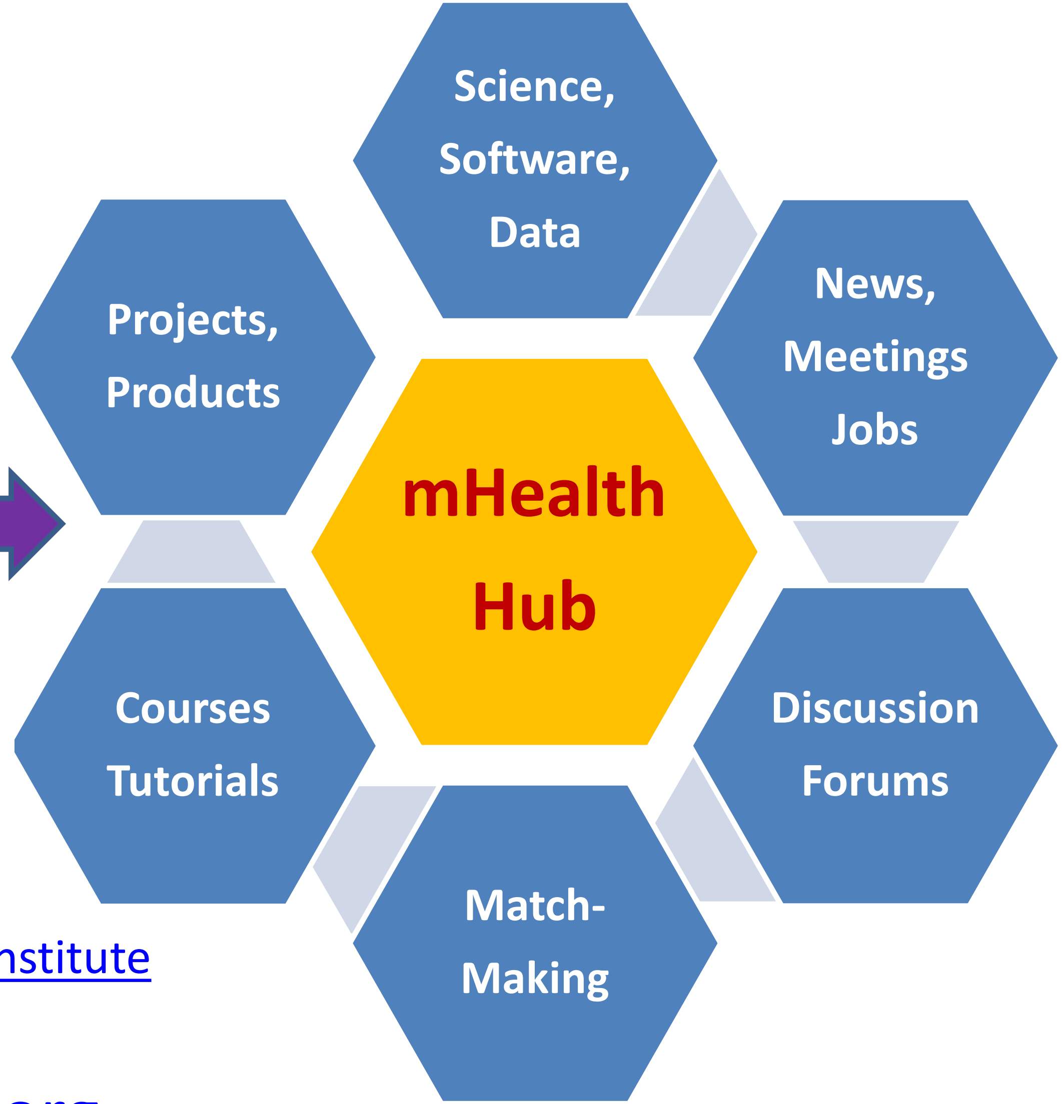
Entire ecosystem (sensors, software, cloud) to be available end of 2017

MD2K Training Resources

github.com/MD2Korg

mHealthHub

mhealth.md2k.org/



mHealth2017
SUMMER TRAINING INSTITUTES

mhealth.md2k.org/mhealth-training-institute

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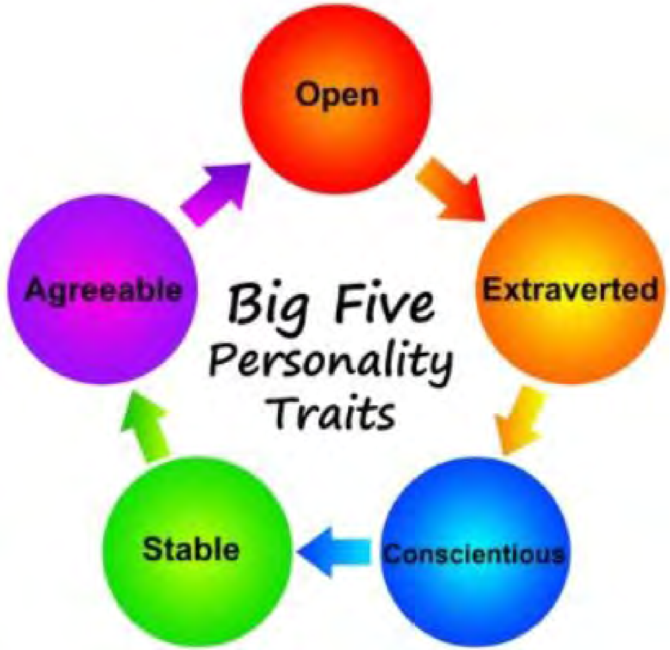
mProv: Provenance Cyberinfrastructure for Mobile Sensor Data

Due to lack of data sharing, everyone needs to collect their own data

Sharing of raw mobile sensor data can accelerate research, but *provenance infrastructure* is needed to enable reproducibility and comparative analysis

Velocity	Variety	Volume	Variability	Veracity	Validation
Hundreds of samples/sec per sensor	Tens of sensors per sensor	Gigabytes per day per person	Variations in attachment, placement, signal quality	Multiple biomarkers from same sensor	Sources of validation for specific biomarkers

Indicators of Everyday Job Performance



CORPORATE CITIZENSHIP

Healthier, Wealthier, and Happier You

Detect → Predict → Adapt

For More Information

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  - 20+ mCerebrum Android applications
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