

Towards Integration of Wearable Sensors for Clinical Outcomes Research

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Outline

- Acute Myocardial Infarction and Heart Failure
- Clinical Outcomes Research in Acute Myocardial Infarction Procedures
- Small Data from Big Data for Remote Sensing

NSF ERC



Vision

To change the paradigm for the health of underserved populations by developing revolutionary and cost-effective technologies and systems at the point-of-care (POC).

Mission

- 1) To engineer transformative, robust, and affordable, technologies and systems to improve healthcare access, enhance the quality of service and life, and reduce the cost of healthcare in underserved populations.
- 2) To recruit and educate a diverse group of scientists and engineers who are ready to lead the future in developing enabling technologies to improve health in underserved communities.

Impact

Bringing affordable point-of-care healthcare technologies and systems to urban and rural underserved communities that lack access to care.

Envisioned Transformative Engineered Systems

Lab on a wrist

- Robust and accurate readings
- data provided to the right stakeholder at the right time
- continuous monitoring
- easy to use

Lab in your palm

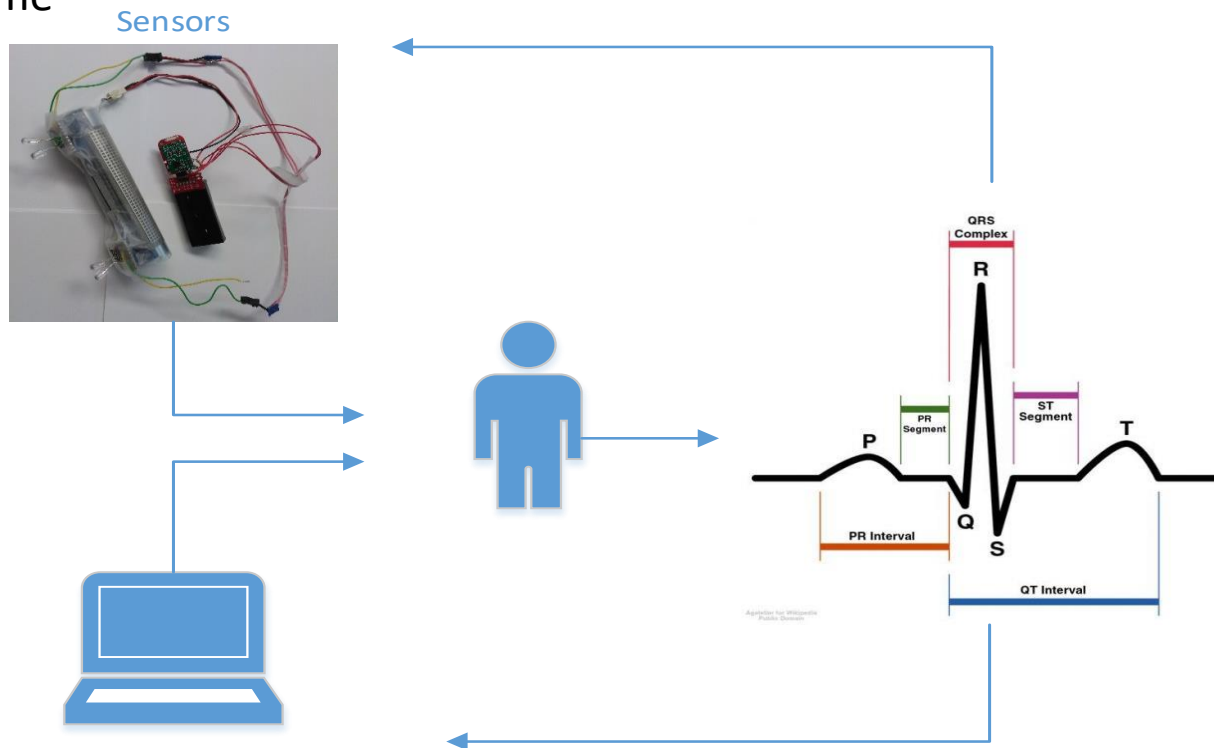
- accurate and sensitive
- minimal sample preparation
- remote diagnostic capability
- inexpensive



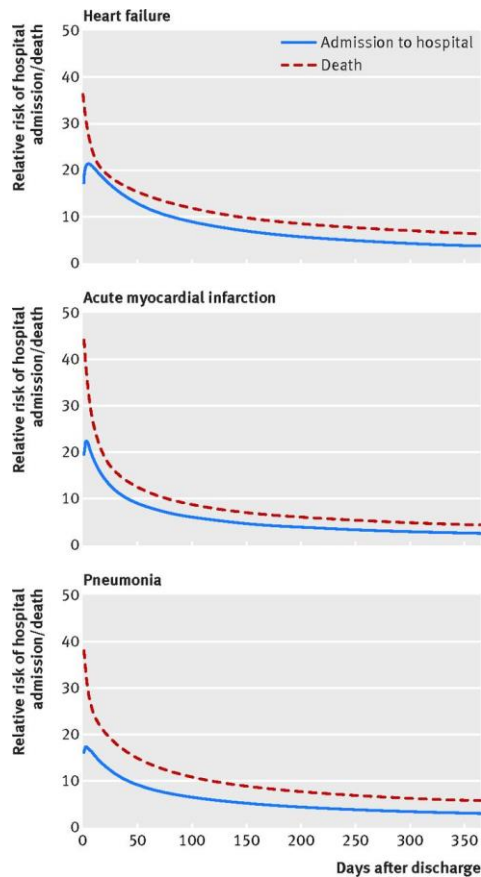
Systems for Personal IOT

Use machine learning models on clinical data to inspire new sensing modalities.

Use personalized data to understand and update models in real-time



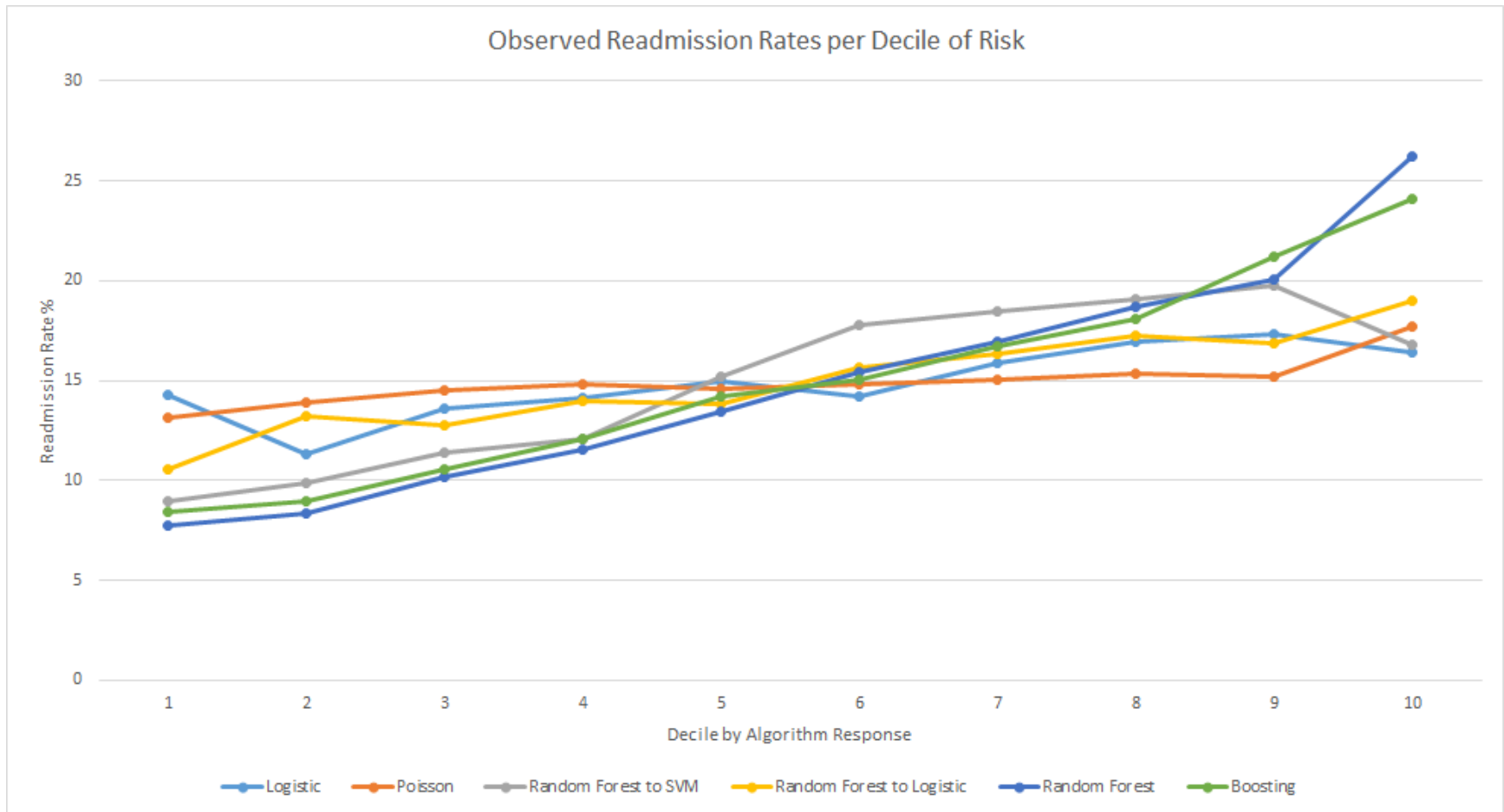
Acute Myocardial Infarction and Heart Failure



(Dharmajan et al. 2015) [1]

- Dharmajan et al. 2015 showed the relative risk for readmission and mortality for a year after hospitalization [1]
- Still, trials that aim to reduce Heart Failure readmissions have been relatively unsuccessful (Tele-HF, Beat-HF) [2][3]
- Big Data/Machine Learning models have modest accuracy in predicting readmissions [4]

Readmission Modeling



Heart Failure and Readmissions

- High Readmission rates impose a tremendous burden on patients and healthcare systems. [5]
- Modeling of recovery has been challenging. [6]
- Cardiac rehabilitation programs have shown promise but low adherence
 - Limited program availability, cost of attending, cost of transportation all impact performance [7][8]
 - Home-based program too hard to follow, or approximate too much and lose individual feedback and engagement [9][10]

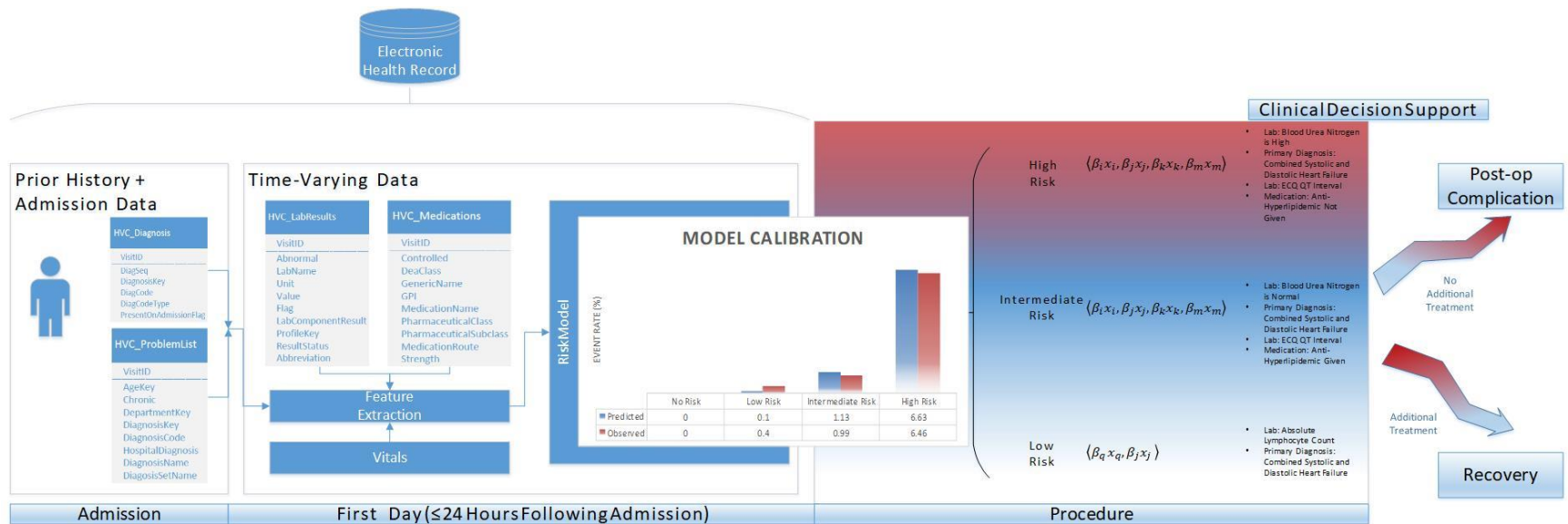
End-to-end systems

- Start with fit patient trending to unfit
- Unfit patient trending to heart attack
- Heart attack causing damage to the heart muscle
- Heart attack needing operation
- Post-operation recovery

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Time-Line



(Mortazavi et al, 2017) [11]

Results

TABLE V

BEST MEAN AUC (95% CONFIDENCE INTERVAL (CI), MODEL) FOR PREDICTING RESPIRATORY FAILURE IN PCI PATIENTS

Test Configuration	Mean AUC (95% CI - Model)	Mean F-score	Mean Top 20 Precision
eRI	0.62 (0.53–0.71, GLM)	0.12 (0.01–0.22)	0.04
windowed eRI	0.63 (0.45–0.81, XGB)	0.15 (0.05–0.24)	0.07
lastRI	0.66 (0.59–0.73, GLM)	0.19 (0.10–0.28)	0.11
windowed lastRI	0.67 (0.48–0.85, XGB)	0.17 (0.07–0.27)	0.08
EHR-RI	0.80 (0.70–0.90, RF)	0.24 (0.11–0.37)	0.00
EHR	0.81 (0.70–0.92, RF)	0.25 (0.12–0.37)	0.00

TABLE VIII

BEST MEAN AUC (95% CONFIDENCE INTERVAL (CI), MODEL) FOR PREDICTING INFECTION IN PCI PATIENTS

Test Configuration	Mean AUC (95% CI - Model)	Mean F-score	Top 20 Precision
eRI	0.72 (0.54–0.89, XGB)	0.10 (0.00–0.20)	0.03
windowed eRI	0.71 (0.54–0.88, XGB)	0.11 (–0.05–0.27)	0.01
lastRI	0.64 (0.43–0.84, XGB)	0.10 (–0.01–0.27)	0.02
windowed lastRI	0.61 (0.54–0.88, XGB)	0.13 (–0.06–0.21)	0.02
EHR-RI	0.81 (0.66–0.95, XGB)	0.12 (0.04–0.21)	0.03
EHR	0.83 (0.72–0.93, XGB)	0.14 (0.04–0.23)	0.04

Cardiac Rehabilitation

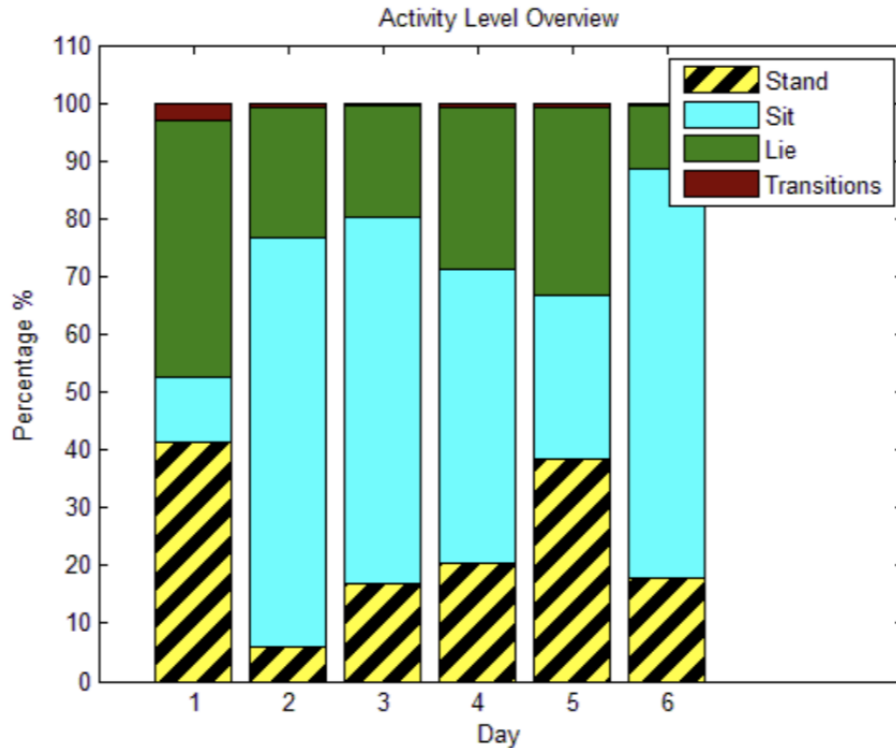
- Heart Rate and V_{O_2}
- Exercise
- Resting Heart Rate, Respiration Rate, and Blood Pressure
- First: Must understand variety of measurements, intensities, and context the data is gathered in

Smartwatch > Smartphones

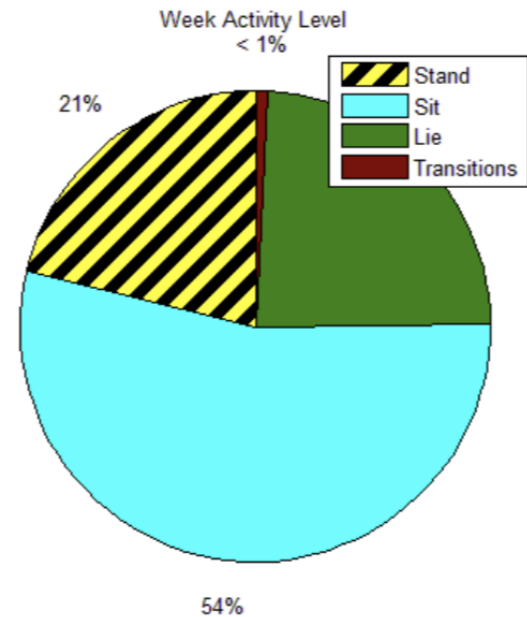
Table 1. Movements Captured

Phase	Movement State	Activity Description
Transitions	Sit - Stand Stand - Sit Sit - Lie Lie - Sit Stand - Lie Lie - Stand	Minimal Movement Transition
Activities of Daily Living	Standing	Using Phone (10 sec) Brushing Teeth (10 sec) Lifting Cup (10 times) Swinging Arms(10 times) Walk (10 sec) Open Door (10 times) Look at Watch (10 times) Clean with broom (10 sec)
	Sitting	Typing (10 sec) Reading Book (10 sec) Brushing Teeth (10 sec) Look at Watch (10 times) Bicep Curl (10 times) Use TV Remote (10 sec)
	Lying	Adjust Pillow (10 sec) Text with phone (10 sec) Adjust in Bed (10 sec) Reading Book (10 sec) Adjust blanket (10 sec)
Walk	Step Forward Step Backward	10 times 10 times

Summarization of Data



(a) Daily transition and state information of a user from the trial

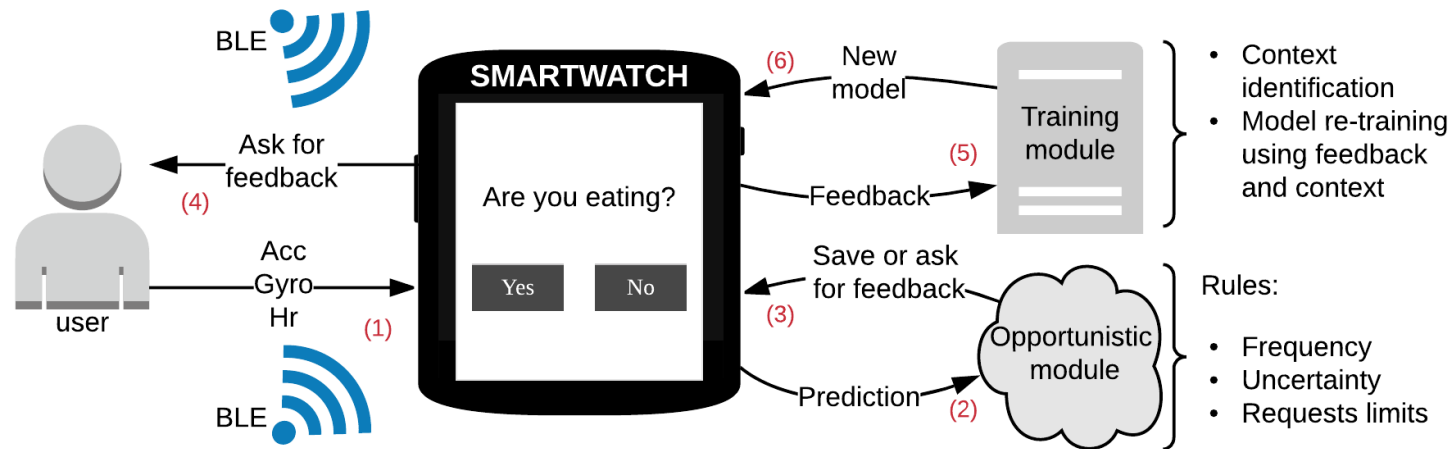


(b) Summary of Week

Important Features

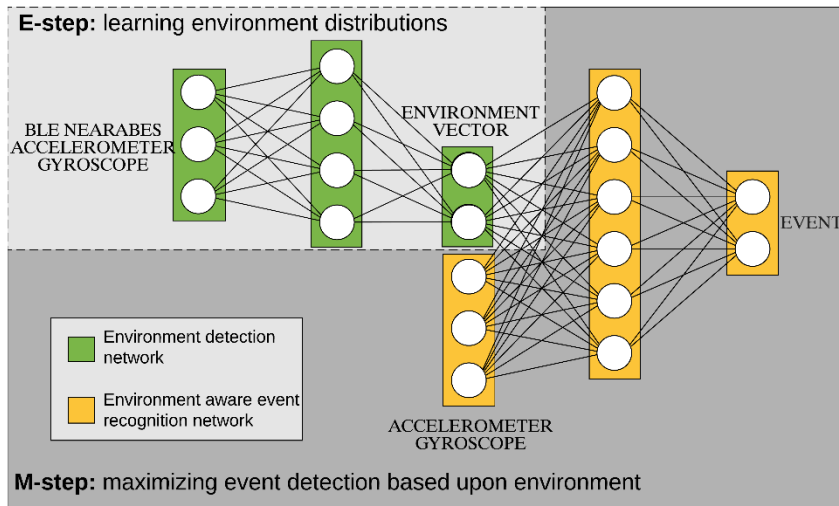
Features 1-10	11-20	21-30
Average Difference (a_x)	Mean (g_y)	Mean (a_x)
Average Difference (a_z)	Sum (g_y)	Sum (a_x)
Median of Intensity of Gyroscope ($\ g\ $)	Eigenvalues (a_x)	Dominant Frequency (g_x)
Mean (g_z)	Root Mean Square (a_x)	Energy (g_x)
Sum (g_z)	Energy (a_x)	Root Mean Square(g_x)
Dominant Frequency (g_z)	Root Sum of Squares (a_x)	Root Sum of Squares (g_x)
Energy (g_z)	Standard Deviation (g_z)	Peak Difference (g_y)
Root Sum of Squares (g_z)	Variance (g_z)	Peak Difference (g_x)
Root Mean Square (g_z)	Variance (g_x)	Dominant Frequency (g_y)
Peak Difference (g_z)	Standard Deviation (g_x)	First Peak (g_z)

Understanding the Context



(Solis et al, 2019, IoTDI) [13]

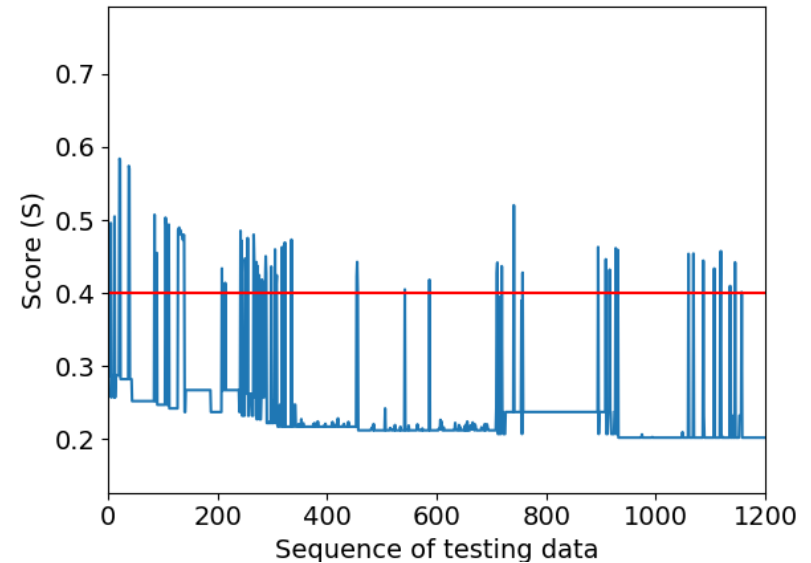
Deep Networks with EM



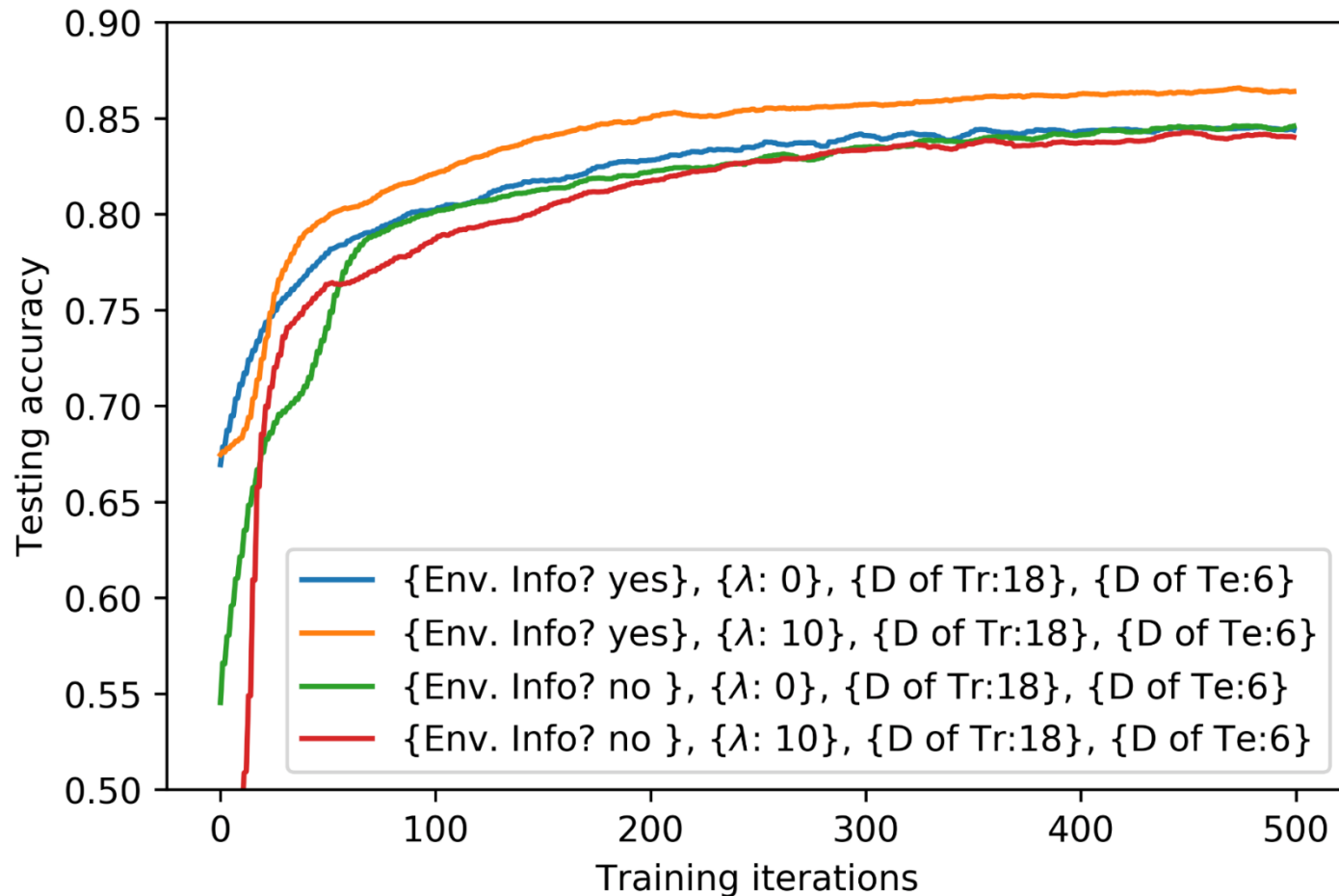
$$\begin{aligned}
 \log P(\text{ACTIVITY}|X, \theta) &= \\
 &= \sum_{n=1}^N \log \sum_{c=1}^{N_c} P(\text{activity}_i, c_i = c | x_i, \theta) \\
 &\geq \sum_{n=1}^N \sum_{c=1}^{N_c} q(c_i = c) \log \frac{P(\text{activity}_i, c_i = c | x_i, \theta)}{q(c_i = c)} \\
 &= \sum_{n=1}^N \sum_{c=1}^{N_c} q(c_i = c) \log \frac{P(\text{activity}_i | c_i = c, x_i, \theta) \cdot P(c_i = c)}{q(c_i = c)} \\
 &= \mathcal{L}(\theta, q)
 \end{aligned}$$

Reducing Labeling Burden

$$D(X) = \begin{cases} 0, & \text{if } \|X - \mu_c^X\| < m * \sigma_c^X \text{ or} \\ & \|X - \mu_{neighbor}^X\| > n * \sigma_{neighbor}^X \\ \frac{\|X - \mu_c^X\|}{\max(\|X - \mu_j^X\|)}, & \text{otherwise} \end{cases}$$



Activity and Context



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Questions?

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