Real-time Adaptive Monitoring of Vital Signs for Clinical Alarm Preemption

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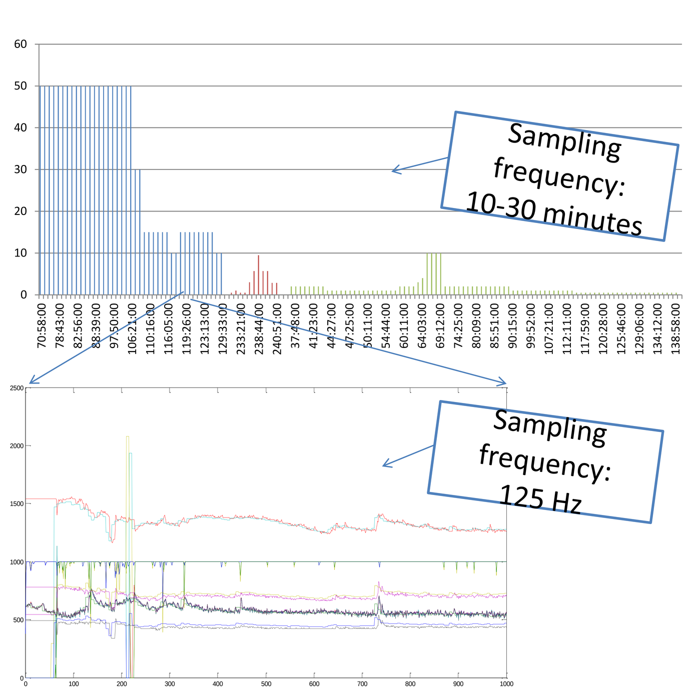
1. Objective

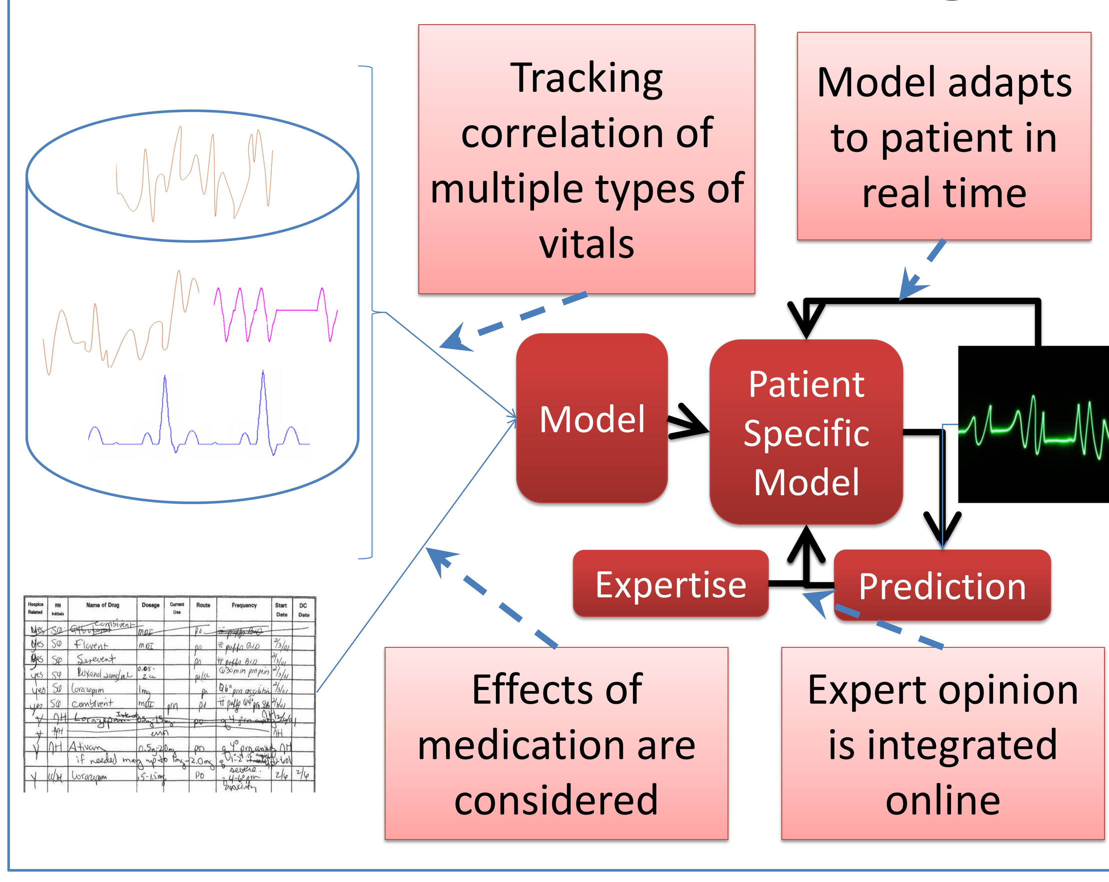
To enable ***prediction of clinical alerts*** via joint monitoring of ***multiple vital signs***, while enabling timely adaptation of the model to particulars of a given patient.

MIMIC II Data

Intensive Care Unit treatment records:
- high-resolution time series - patient vitals
- low-resolution time series - medication



2. Overview of the Vital Sign Monitoring System



Novelty of approach

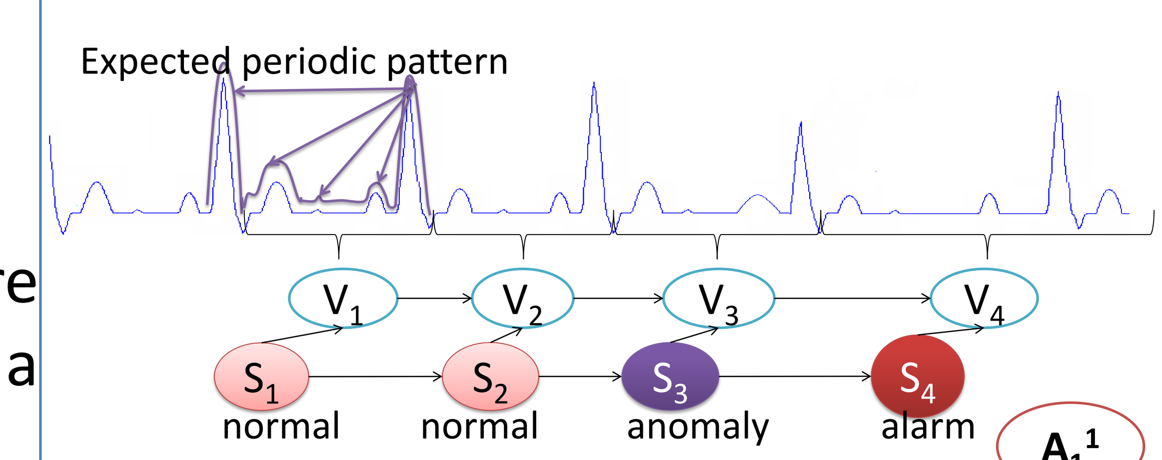
- ***Unsupervised*** signal segmentation
- Tracking of ***multiple vital signs***
- Models ***online-adaptable*** using ***patient-specific*** feedback signals
- Models incorporate effects of ***medication*** on state changes
- Models can incorporate ***expert feedback***

3. Model

Learning

- Vitals are adaptively segmented to reflect signal periodicity
- The segmented vitals are then represented with a continuous Semi-HMM
- The arity of the state var. is obtained via EM
- Treatment - vector of administered medications - influences the output

Level 1: Vital Segmentation



V – observed vital signs

S – signal state learned from vitals

- one set of values per period
- encodes duration and transitions
  - $V_{1:N-1} = \tau V_{2:N}$
  - $\tau | S \sim \mathcal{N}(\tau_0(s), \Sigma(s))$

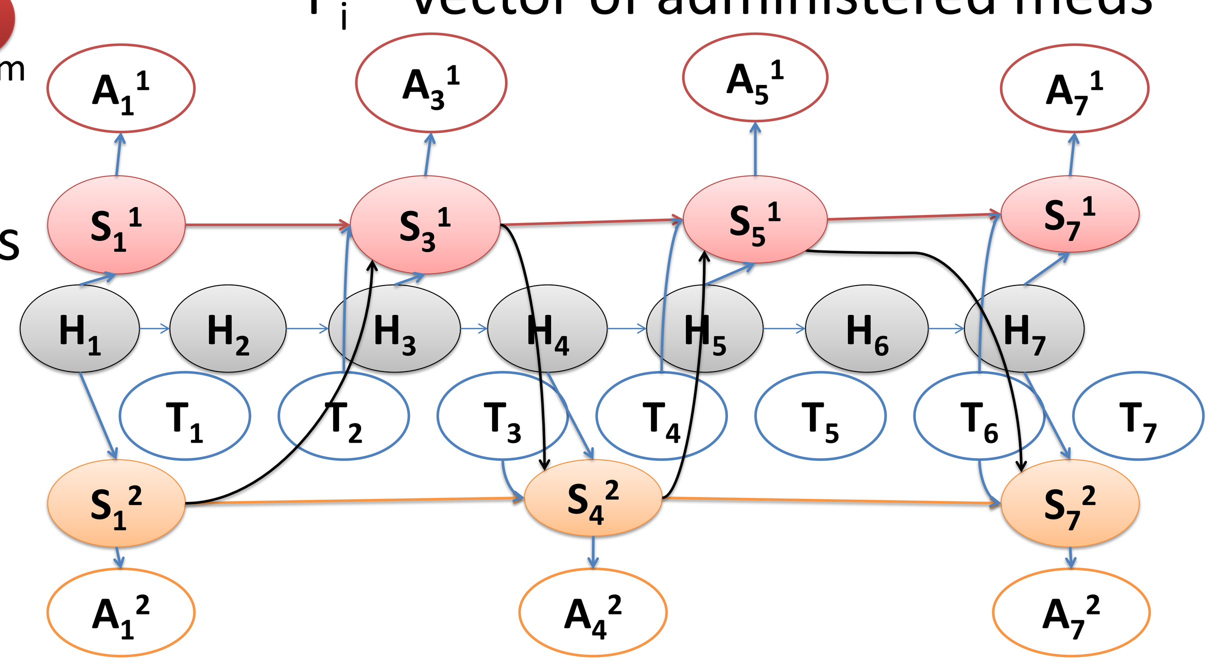
Level 2: Health Status Model

A – alarms observed when active

S^1, S^2 –states of different vitals

H_i– current state given previous states of multiple vitals

T_i – vector of administered meds



Inference, online update

- Real-time alarm prediction from previously observed vitals
- Online learning from user feedback (correct labels of the predicted states)

s = state of current period

If the alarm signal is not 1:

- τ_0 = update_mean(τ_{prev}, s)
- Σ = update_stdev(Σ_{prev},s)

Update H:

- adapt $S_i^j | S_{i-1}^1, S_{i-1}^2, A^j, T$

Segmentation

ECG and Blood Pressure can be well segmented.

Vital Signs	Log-likelihood of segmented vital sequences according to the learned patient-adaptive model					
	Patient 1		Patient 2		Patient 4	
	Test	Train	Test	Train	Test	Train
ECG	0.346	0.346	4.629	4.030	0.380	0.449
Respiratory Rate	0.338	0.295	0.413	0.459	0.283	0.295
Blood Pressure (mean)	0.429	0.429	0.376	0.309	0.284	0.295
Blood Pressure (systolic)	0.395	0.395	x	x	0.283	0.295
Blood Pressure (diastolic)	1.245	7.925	x	x	0.207	19.065

4. Results

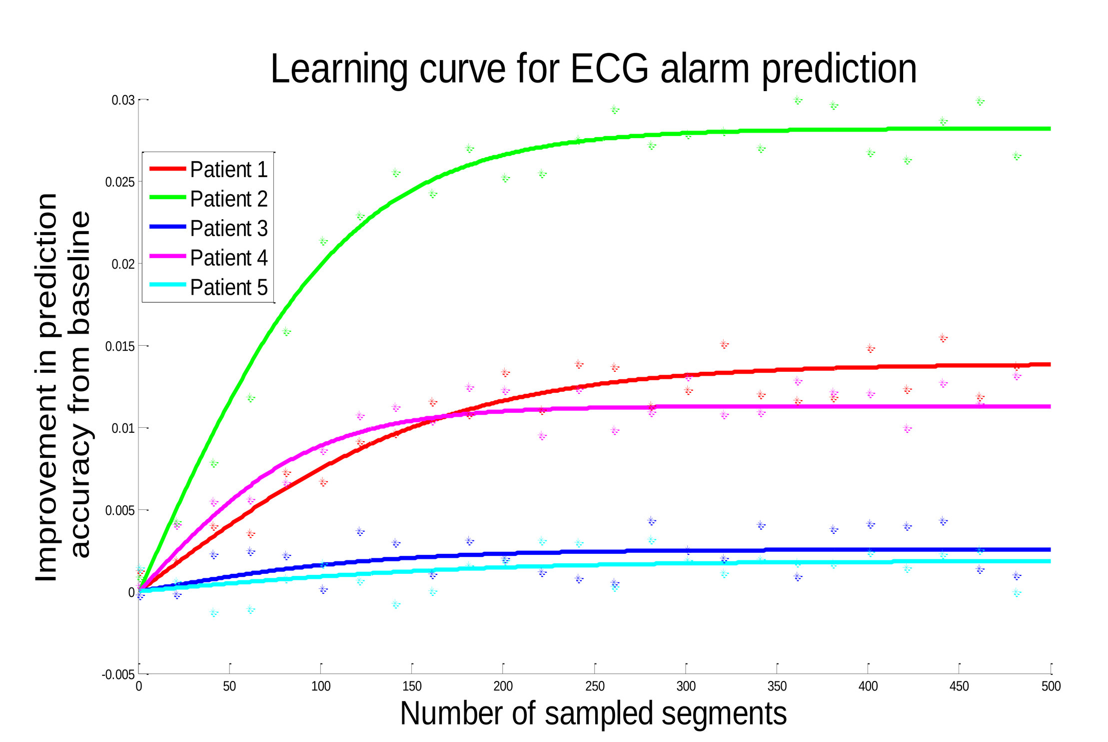
Alarm Prediction:10 minutes in advance

Online adaptation of the model to patient data improves accuracy, as does inclusion of medication in the model.

AUC = Area Under ROC Curve			
Patient	AUC of unadapted model	AUC of patient-adapted model	AUC of treatment-enhanced model
1	0.67	0.68	0.70
2	0.61	0.63	0.65
3	**0.71**	**0.72**	0.72
4	0.64	0.65	0.71
5	0.70	0.70	**0.73**

Learning Curve

It takes ~ 5 minutes for the model to adapt to a patient when labels are available.



Dependency

$$Improvement(x) = \frac{C}{1 + \exp - \frac{x}{x_{opt}}}$$

x- number of samples

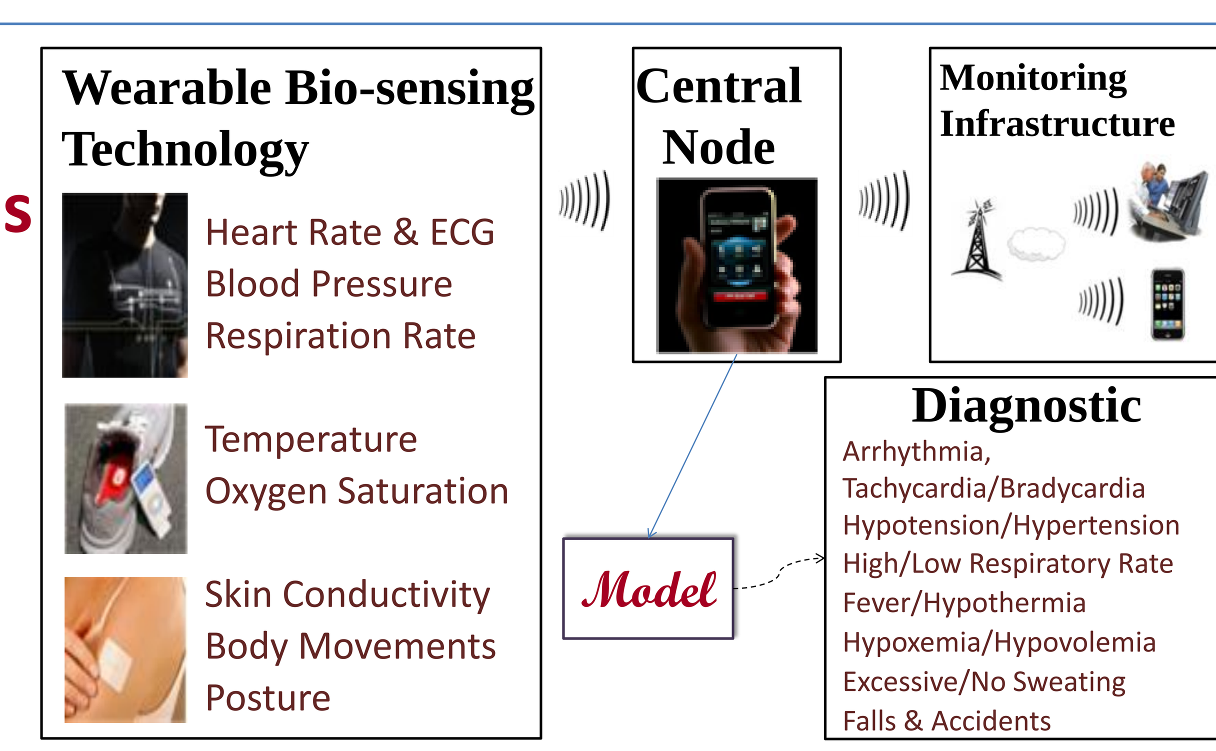
x_{opt} – required to achieve best model

5.Conclusions

- We prototyped a **probabilistic model** that **predicts heart failure alarms** from vital signs
- The system is able to learn the **key parameters** from data (state and temporal resolution)
- The system enables **real time**, incremental learning of more accurate **personalized models**

6.Future Work

- Identify **anomalies**
- Integrate **expert feedback**
- Incorporate prediction in **wearable system**



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Successful online adaptation for personalized detection of heart failure