



*1st Invitational Workshop on*  
**Body Area Network Technology and Applications**  
Future Directions, Technologies, Standards and Applications  
June 19-20, 2011  
Worcester Polytechnic Institute

***From Embedded DSP to Embedded AI:  
making chronic patient monitoring  
intelligent and scalable***

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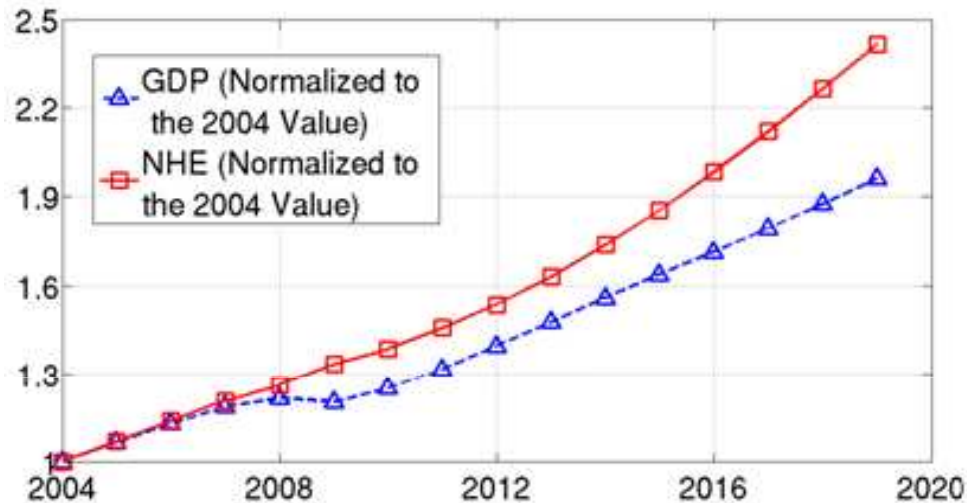
**Body Area Network Technology and Applications**  
**WPI**

**Naveen Verma**

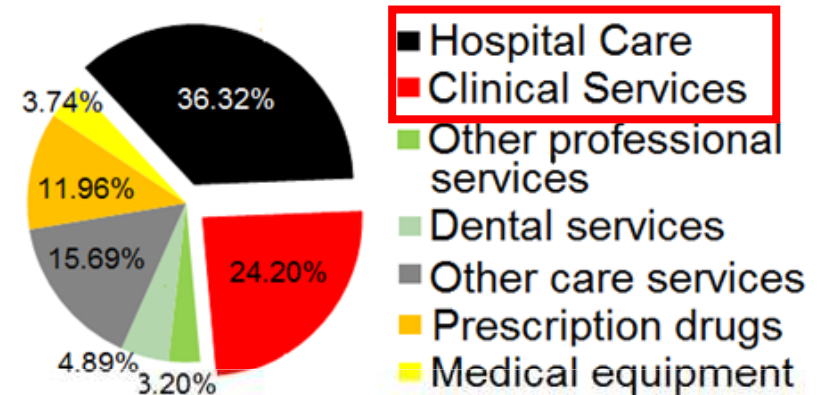
**[nverma@princeton.edu](mailto:nverma@princeton.edu)**

# Healthcare: a problem of scale

## Anticipated US GDP and NHE



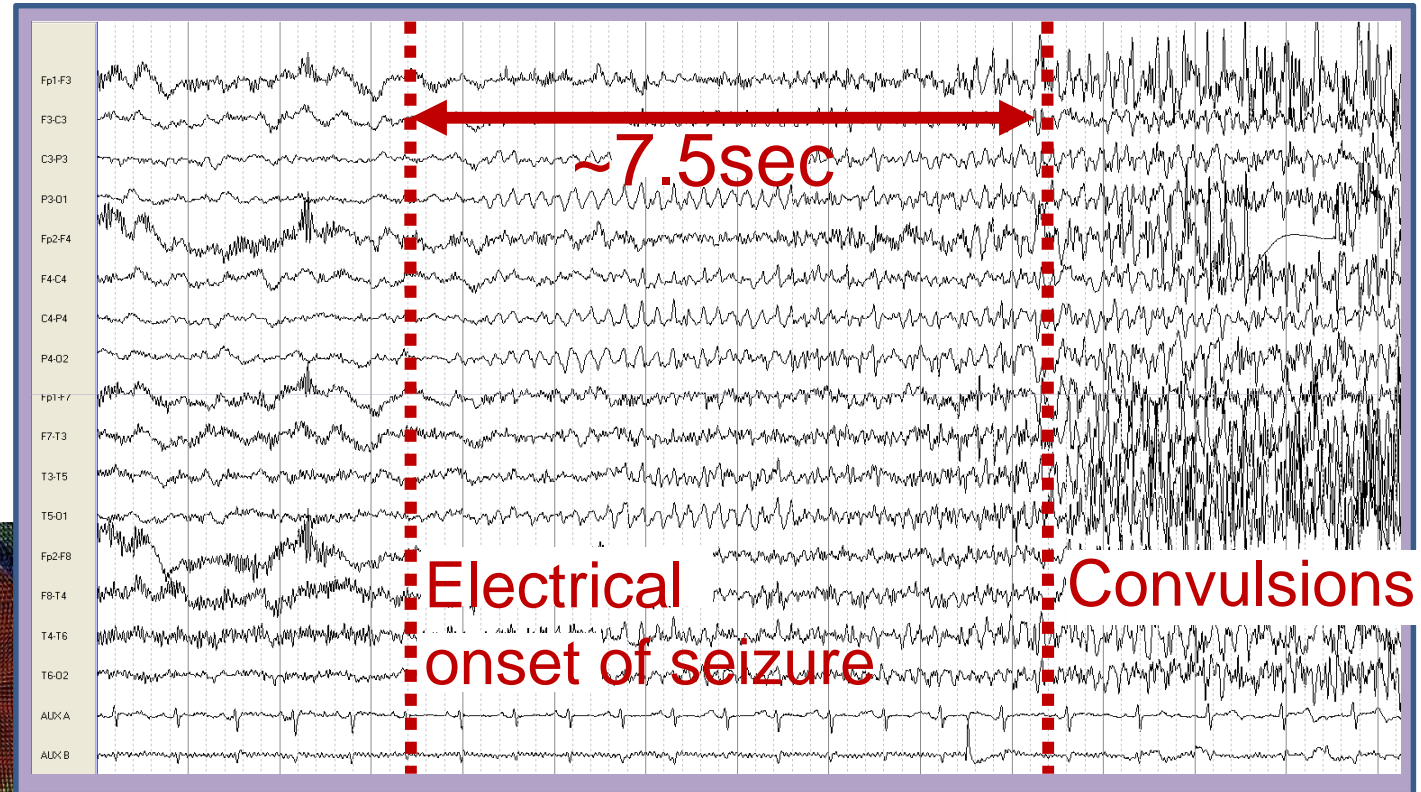
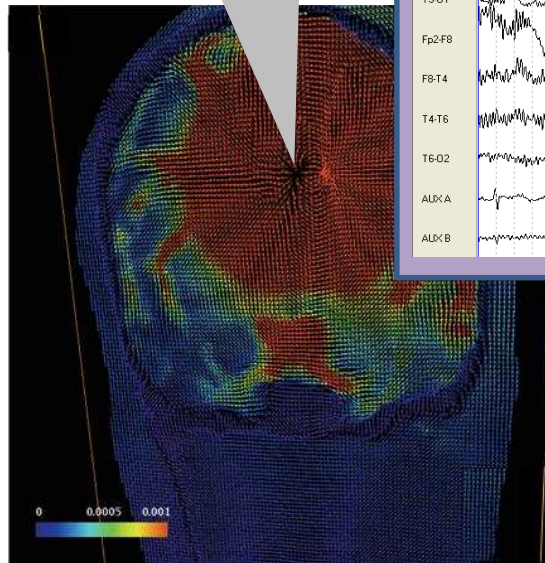
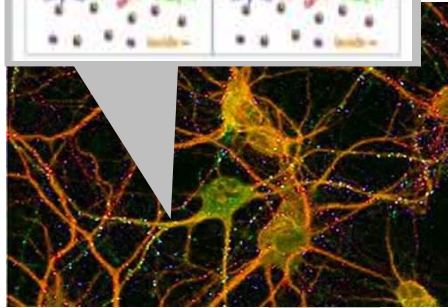
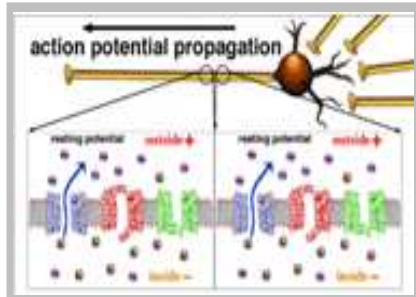
## NHE breakdown



- 60% is due to hospital/clinical visits
- 75% (\$1.3T) is due to management of chronic disease and conditions (chronic disease causes 70% of deaths)

Aim is to translate scalability of technology  
**into scalability of clinical responsiveness**

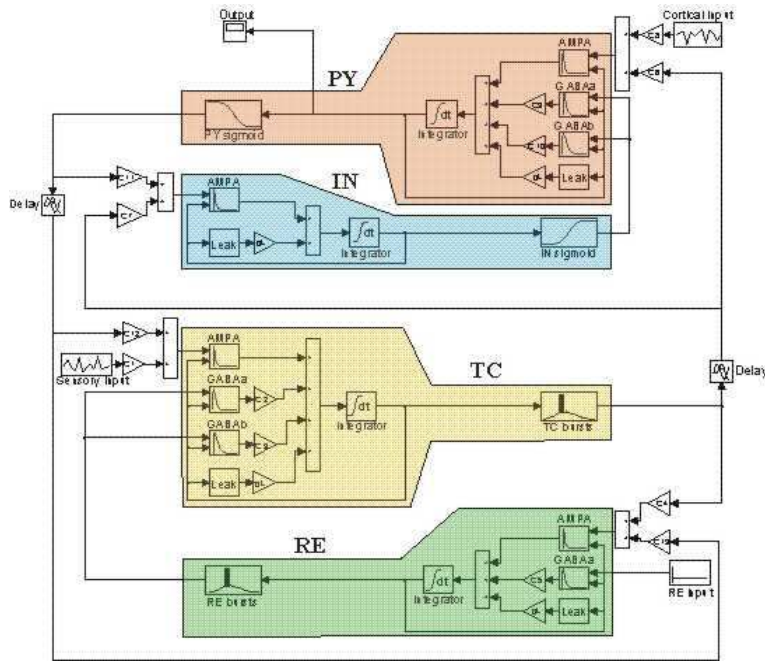
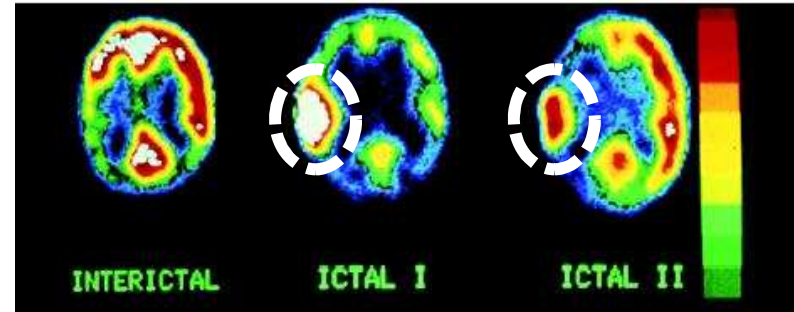
# Clinical inference: what does this signal mean?



# Why is it hard? (I)

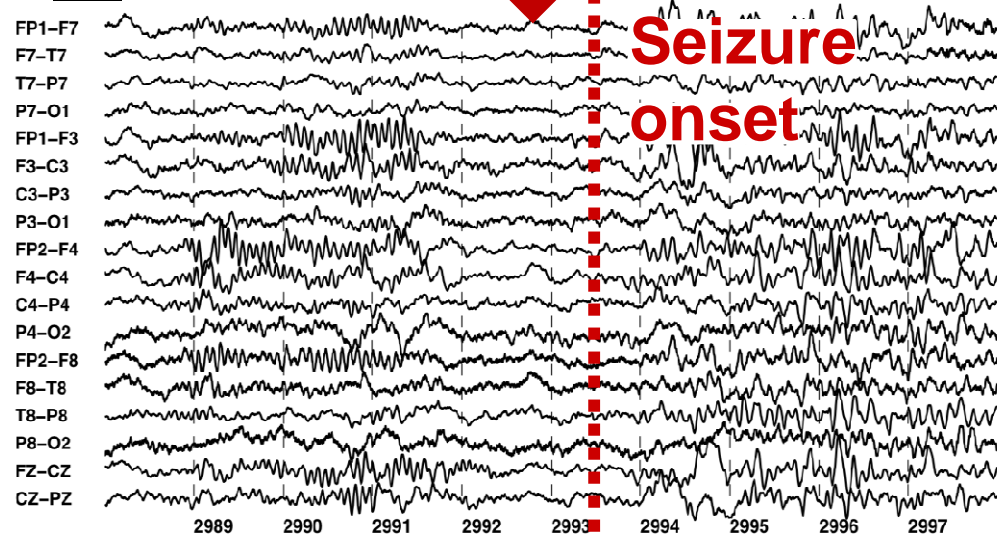
**Signals from low-power chronic sensors are non-specific**

**Single-photon emission computed tomography (SPECT)**



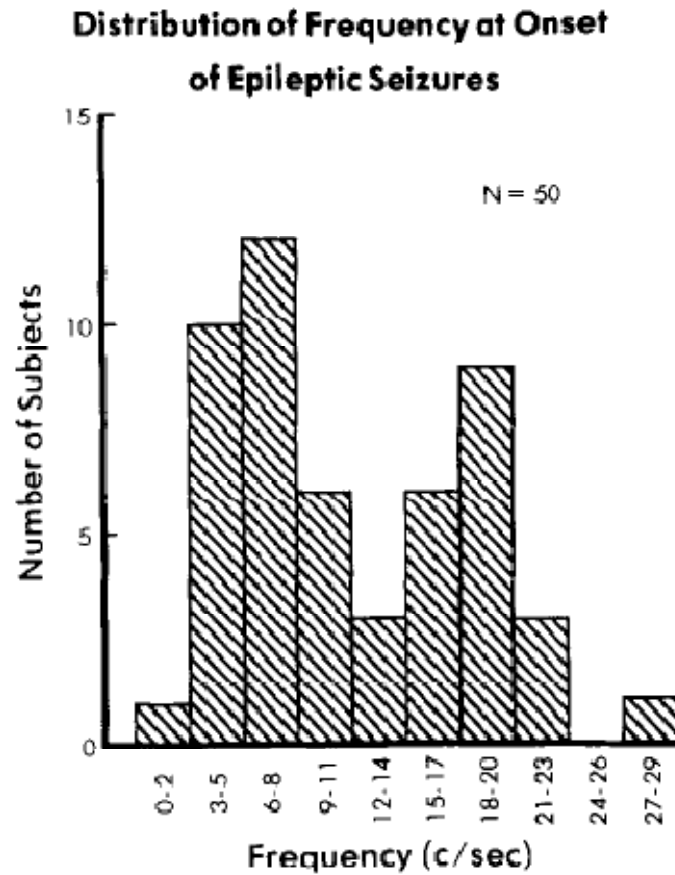
[Suffczynski, *Neuroscience*'04]

**EEG**



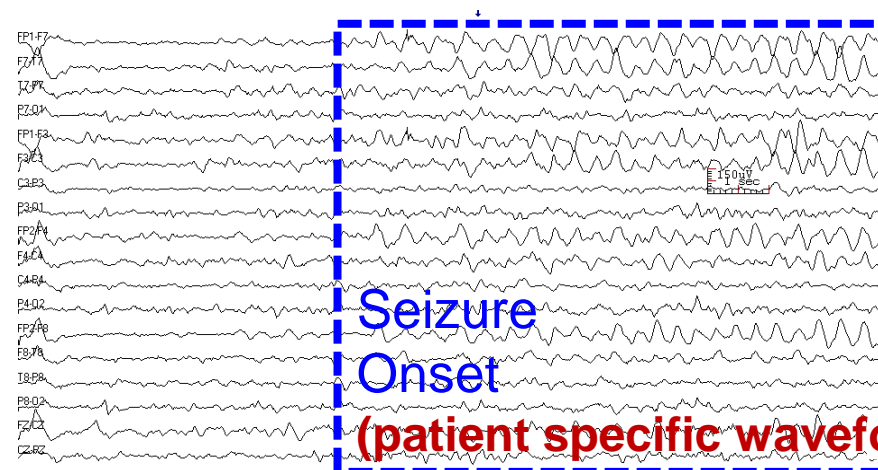
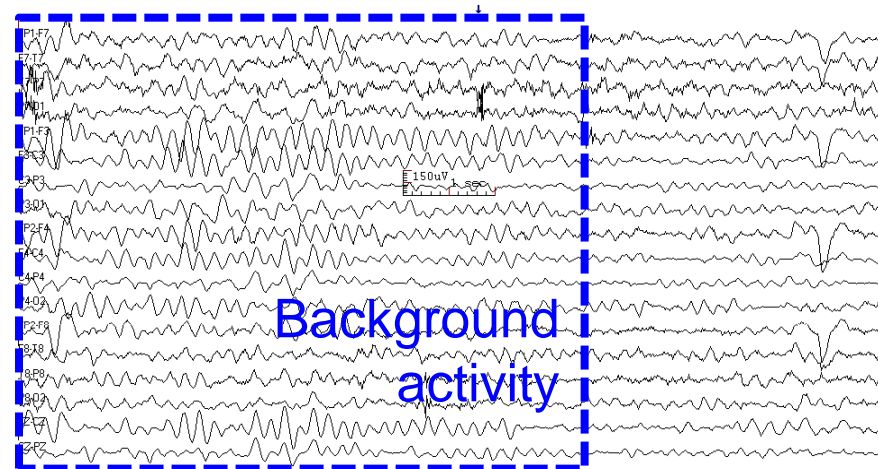
# Why is it hard? (II)

**Expression of disease states is variable over patients & time**



[Gotman, *EEG & Clinical Neurophys.*'81]

**Patient A EEG:**



# Constructing and applying high-order models

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## Enabling data-driven patient-monitoring networks through...

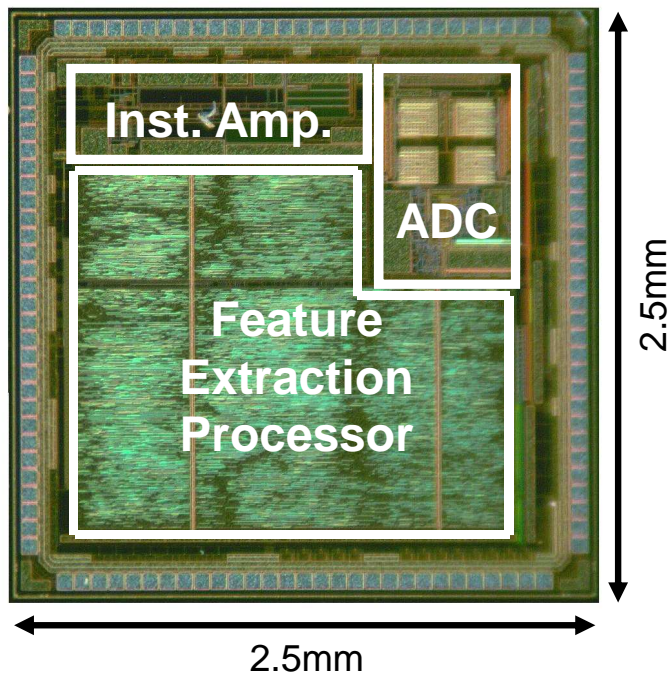
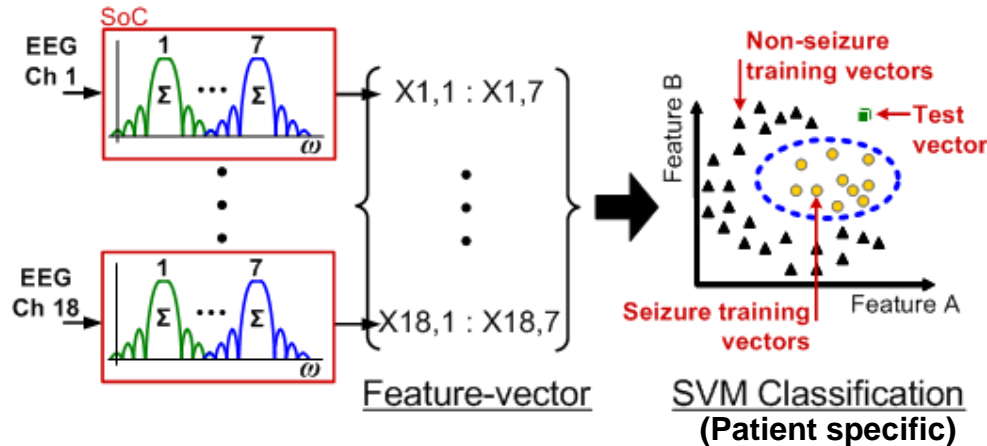
### 1) Efficient techniques for data analysis

- Utilize methods from the domain of supervised machine-learning
- Embed these in low-power platforms and devices

### 2) Availability of physiological data

- Exploit patient databases from the healthcare domain
- Exploit data acquisition capability of the sensor network

# Towards devices: seizure detection IC

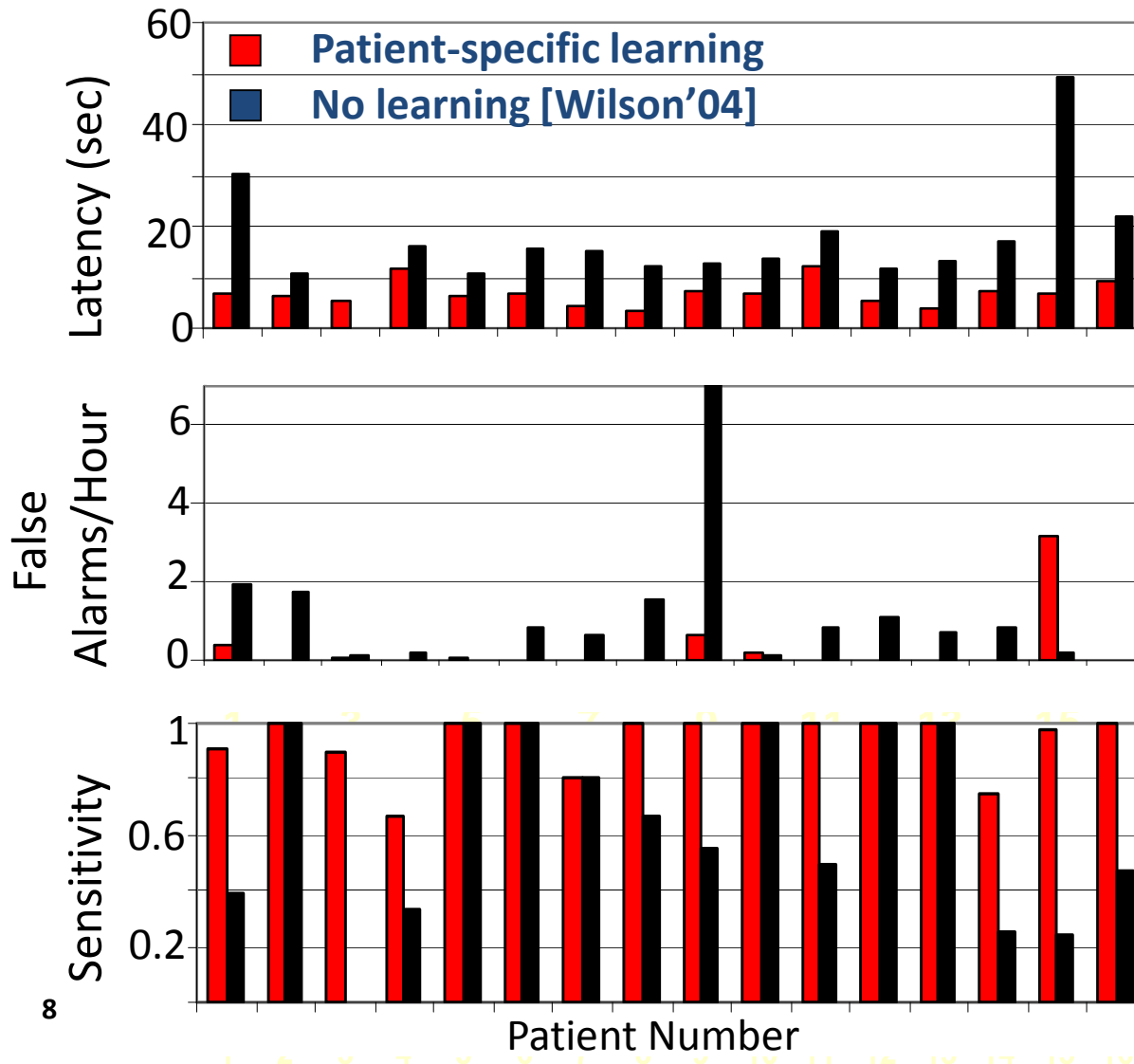


Supply voltage	1V
I-amp LNA power	3.5 $\mu$ W
I-amp input impedance	>700M $\Omega$
I-amp noise (input referred, 0.5Hz-100Hz)	1.3 $\mu$ Vrms
I-amp electrode offset tolerance	>1V
I-amp CMRR	>60dB
ADC resolution	12b
ADC energy per conversion	250pJ
ADC max. sampling rate	100kS/s
ADC INL/DNL	0.68/0.66LS B
ADC SNDR	65dB
Digital energy per feature-vector	234nJ
Feature vector computation rate	0.5Hz
<b>Total energy/feature-vector per EEG channel</b>	<b>9<math>\mu</math>J</b>

[JSSC, April'10]

# Impact of patient-specific modeling

**536 hrs of patient tests:**



**Latency:**

- Specific:  $6.77 \pm 3.0$  sec
- Non-sp.:  $30.1 \pm 15$  sec

**False alarms:**

- Specific:  $0.3 \pm 0.7$  /hr
- Non-sp.:  $2.0 \pm 5.3$  /hr

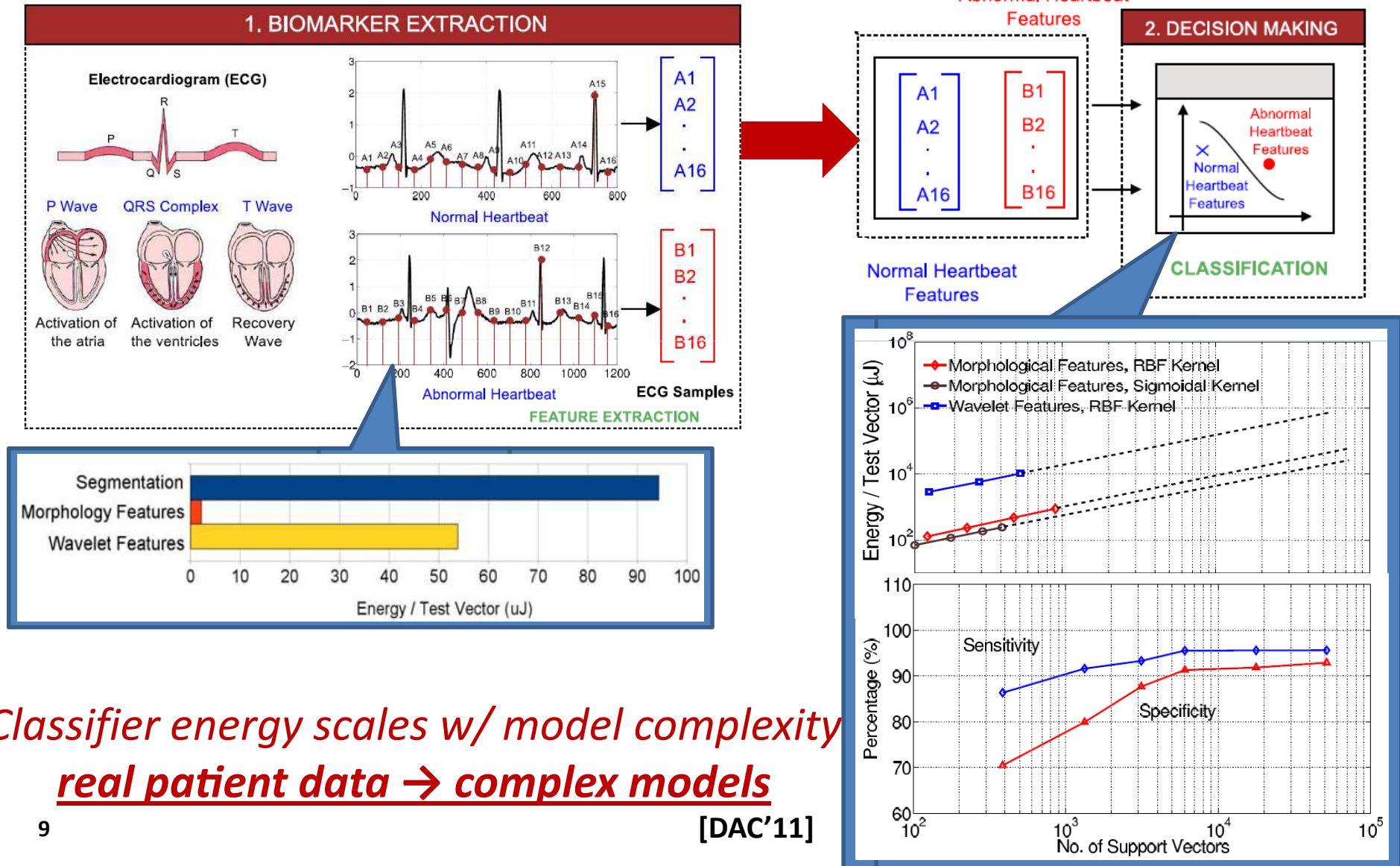
**Sensitivity:**

- Specific: 0.93
- Non-sp.: 0.66

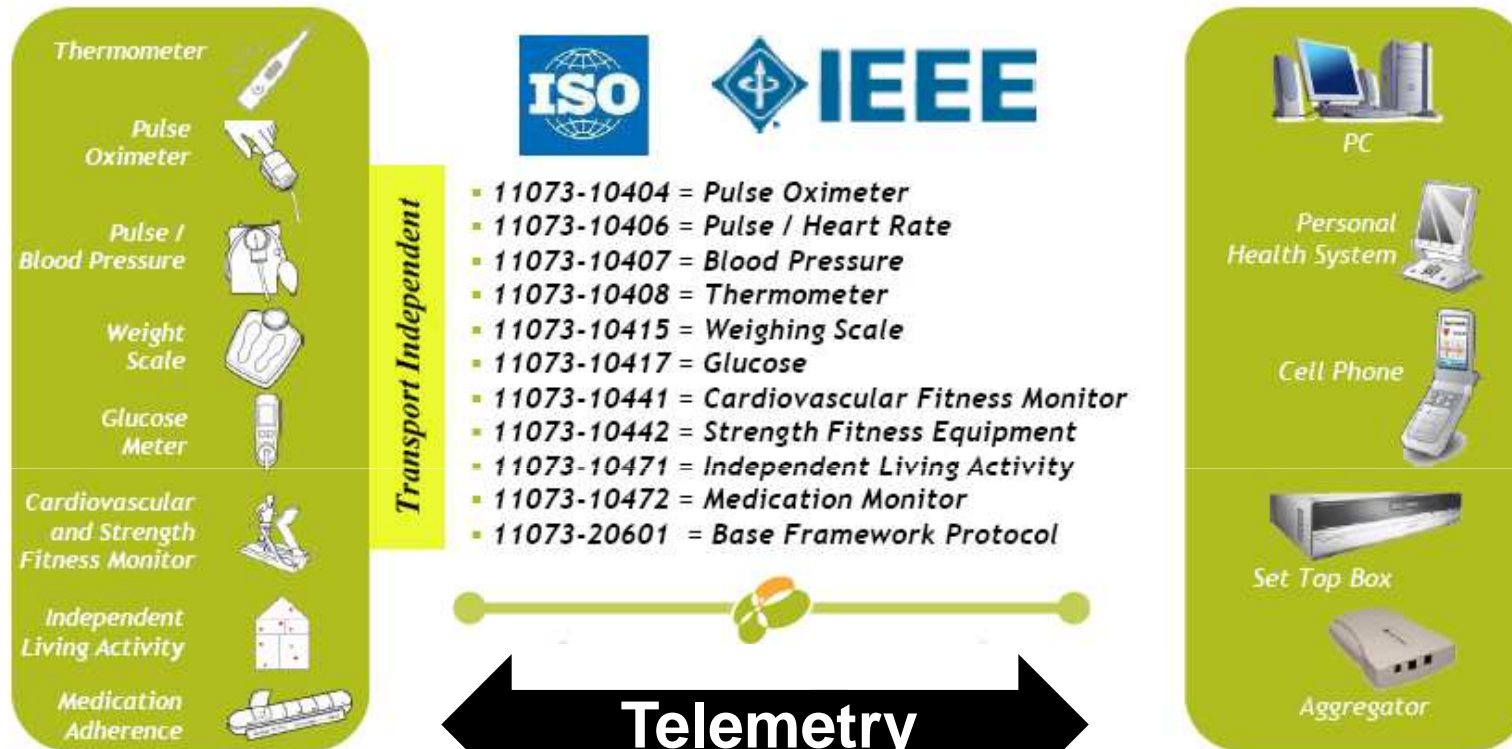
[Shoeb, EMBC'07]



# Computational energy: ECG beat detection



# Expanding the standards



[www.continuaalliance.org](http://www.continuaalliance.org)

# Summary

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Physiological expressions in low-power sensing modalities  
Are non-specific and variable from patient-to-patient



Data-driven methods provided systematic approaches for  
constructing high-order models

Need:



Algorithms

(identify data instances  
to present to experts)



Platforms

(exploit algorithmic  
structure for low  
energy & flexibility)



Networks

(selective utilization of  
clinical resources)