

Bridging the Gap from Semiconductors to Medical Technologies:

GE Advances in Multiparameter Gas, Physiological, Biological Sensing

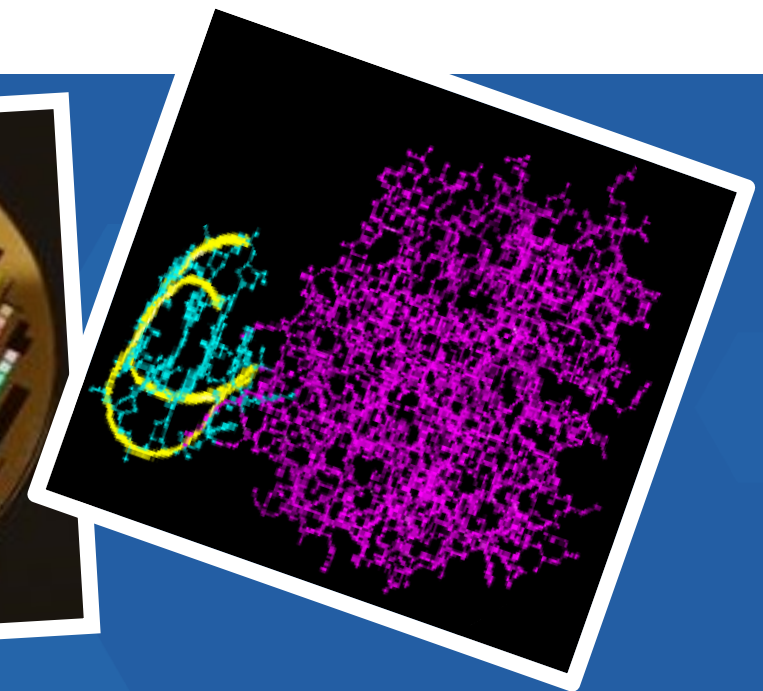
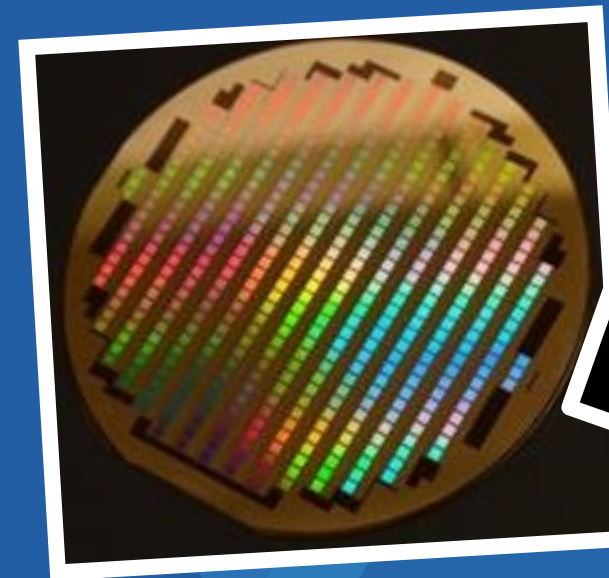
Radislav A. Potyrailo, PhD

Principal Scientist

Hilary Lashley Renison, MS, MBA

Senior Business Development Manager

GE Research, Niskayuna, NY, USA



Outline

Current state and remaining challenges in wearable sensors

Value of high-performance sensors

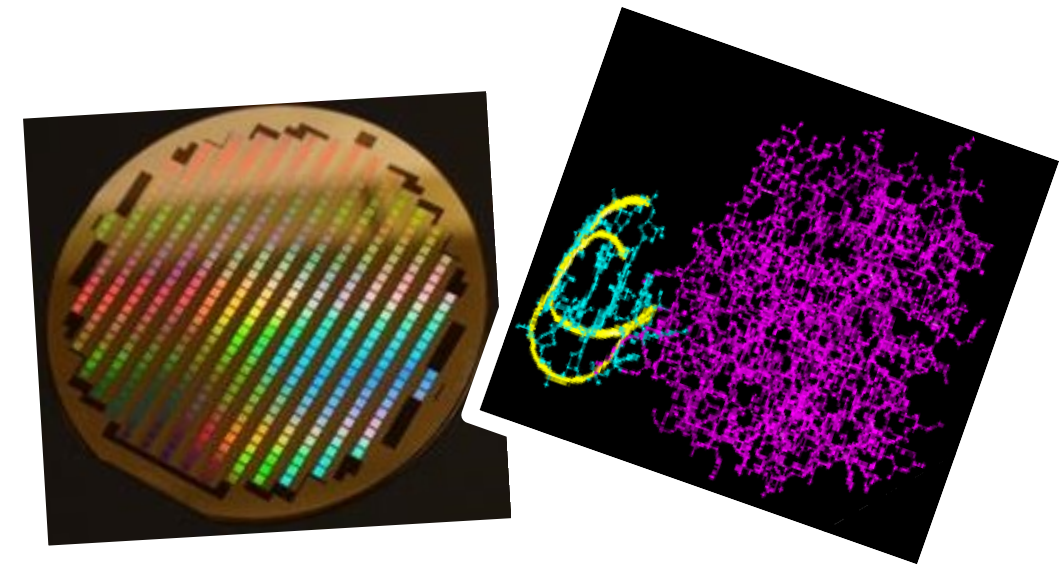
Examples of GE advances:

- Multiparameter gas sensing

- Physiological sensing

- Biological sensing

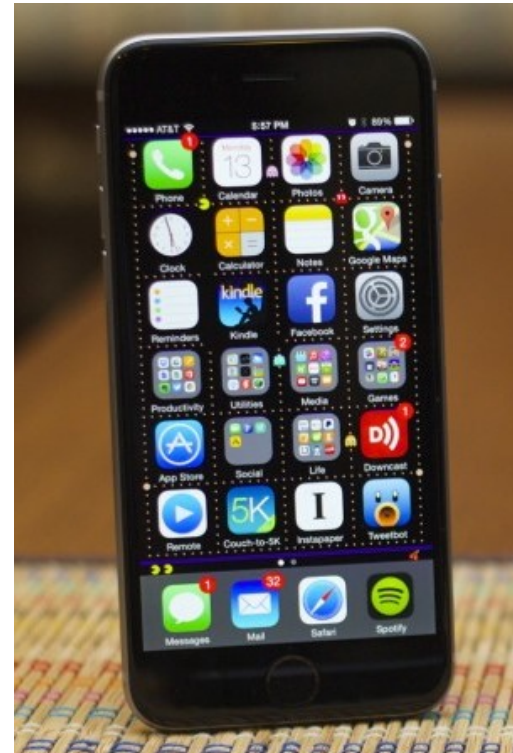
Future developments



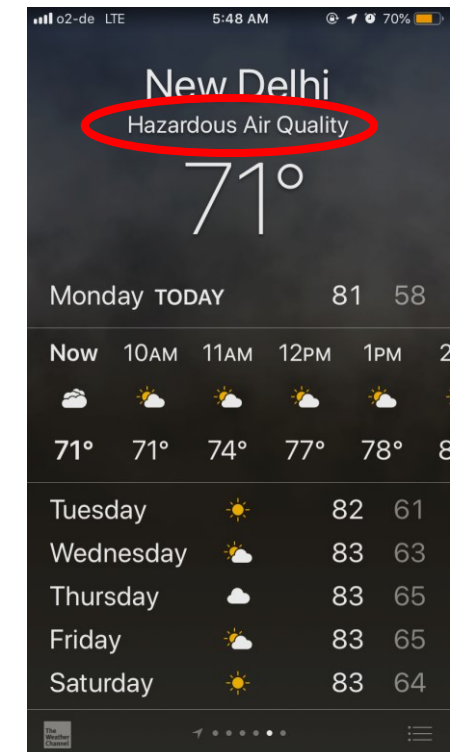
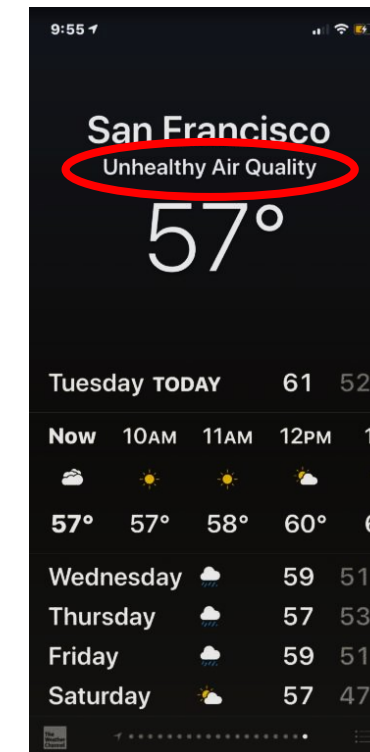
I like my mobile phone

- ✓ Microphone / speaker
- ✓ Touch screen
- ✓ Screen orientation
- ✓ GPS
- ✓ Weather
- ✓ Air pollution
- ✓ Etc....

Use of internal sensors



Display of readings of other sensors

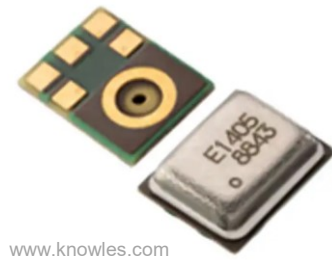


Reliable sensors on board,
wireless connectivity to reliable knowledge

Physical sensors for mobile applications

Examples of sensors with annual sales of billions of units

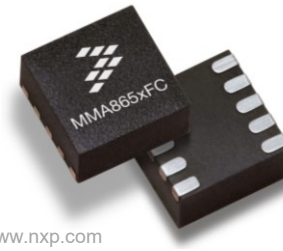
Microphones



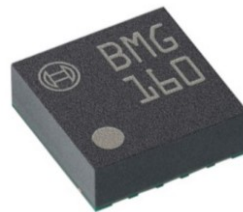
Pressure sensors



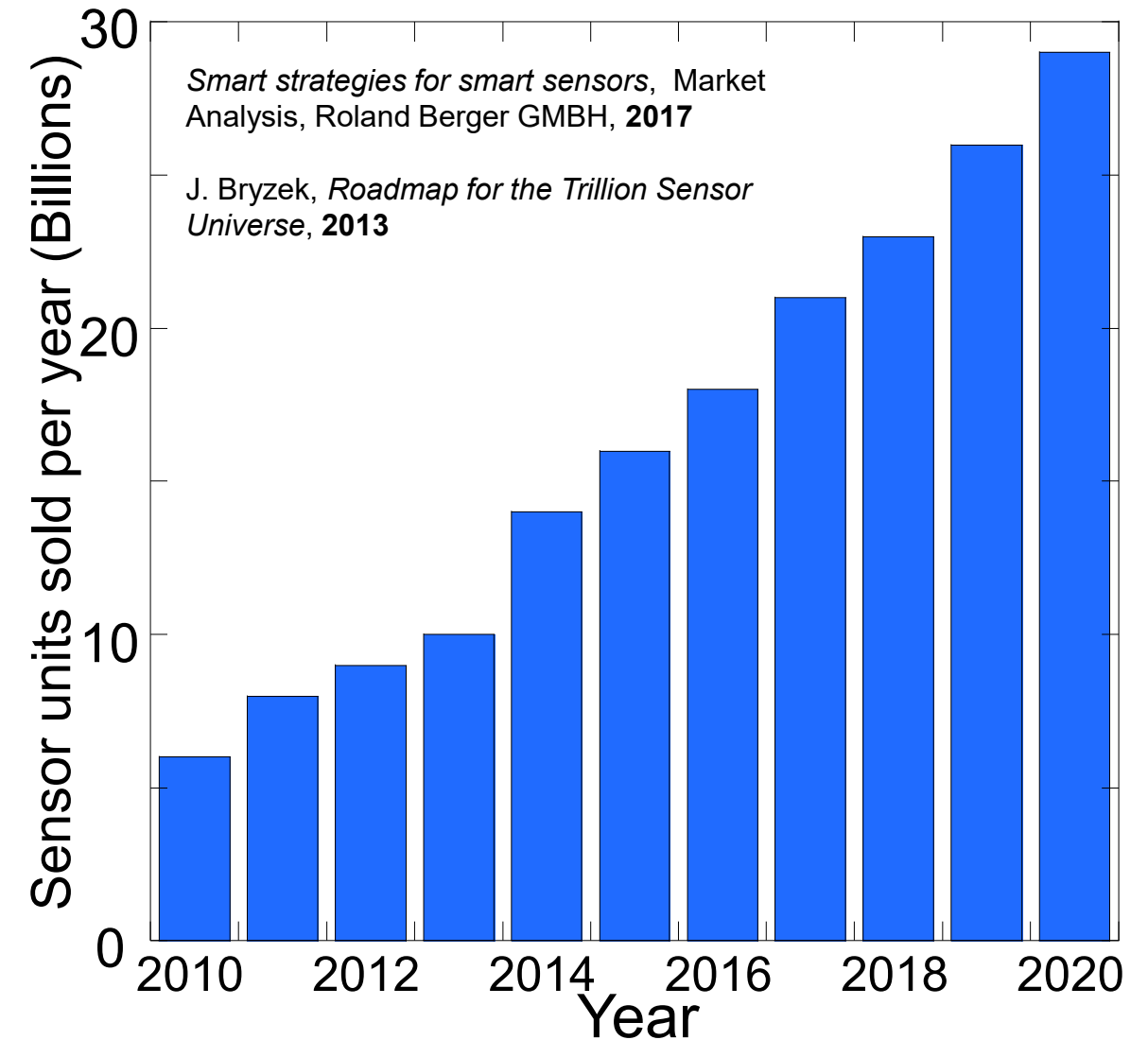
Accelerometers



Gyroscopes



Compasses



High sensor reliability leads to demand of billions of sensors per year

I like my wearable heart rate monitor

Garmin
Forerunner 235



[amazon.com](https://www.amazon.com)

Apple
Watch



Great gadgets to motivate me
to do workout...

I like my wearable heart rate monitor

Garmin
Forerunner 235



amazon.com

Apple
Watch



For The Wearable Revolution To Take Off, Accuracy Must Improve

CVC, *Inside Activity Tracking*, 2013



<http://www.insideactivitytracking.com/tracking-accurately-how-is-it-done-why-is-it-difficult/>

Fitness Wearables Lack Accuracy

C.Van Hoof, *EE Times*, 2014



http://www.eetimes.com/author.asp?section_id=36&doc_id=1321976

The Struggle for Accurate Measurements on Your Wrist

R. Metz, *MIT Technology Review*, 2015



<https://www.technologyreview.com/s/538416/the-struggle-for-accurate-measurements-on-your-wrist/>

Real world wrist-based heart rate monitor test: Are they accurate enough?

S. Richmond, *Wareable*, 2015



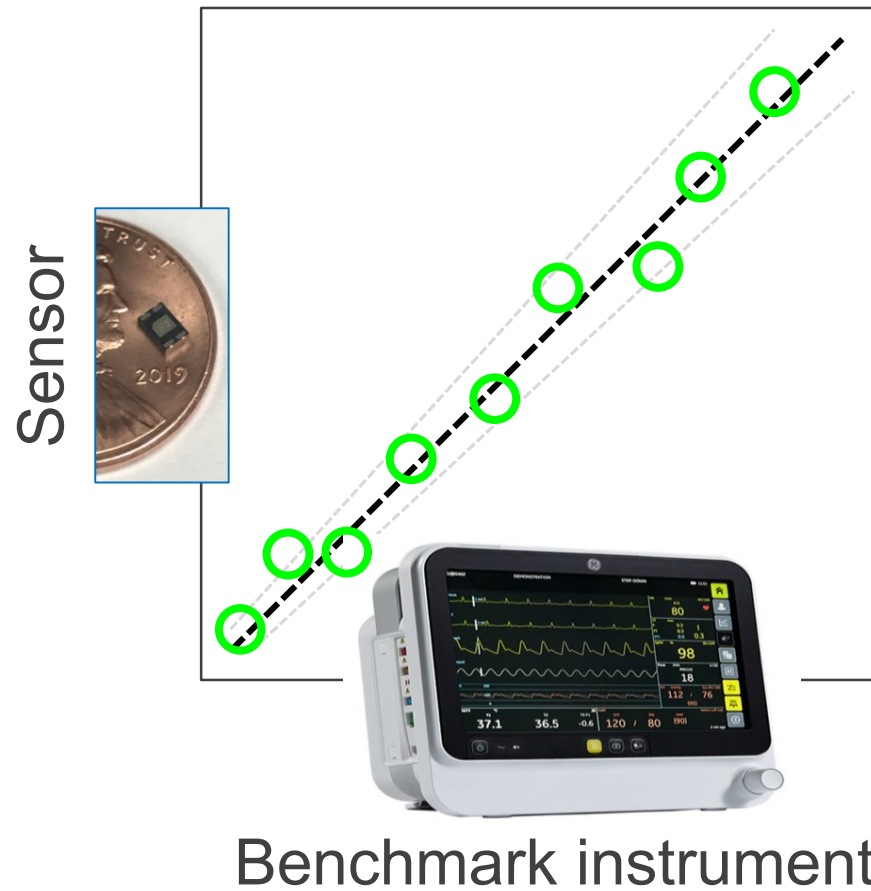
<http://www.wareable.com/fitness-trackers/heart-rate-monitor-accurate-comparison-wrist>

Great gadgets to motivate me to do workout...

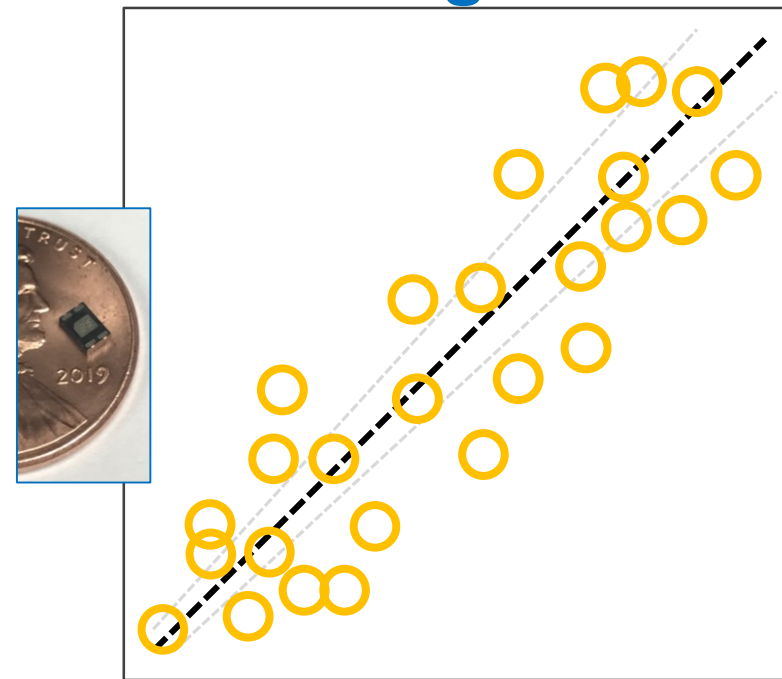
The remaining challenge in wearable sensors:
“For the wearable revolution to take off, accuracy must improve”

Accuracy: Correlation between benchmark instruments and new sensors

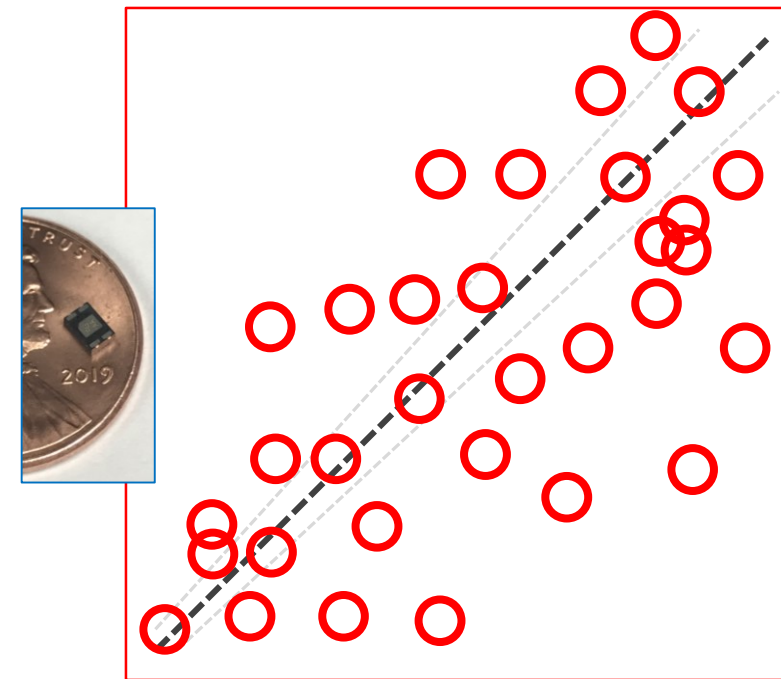
Good



Marginal



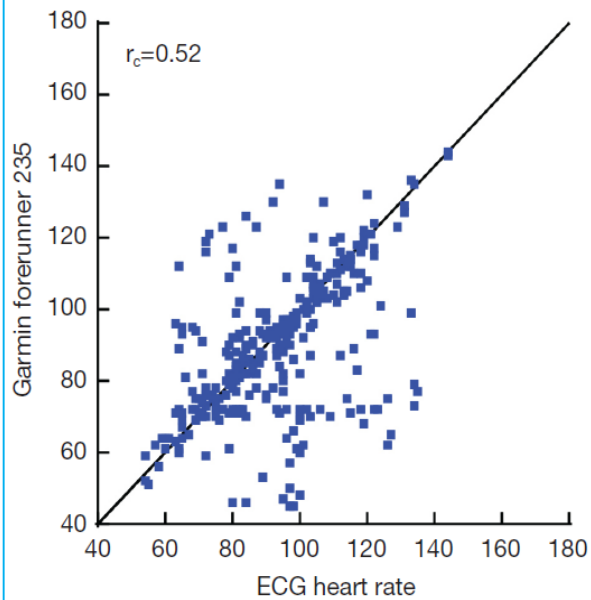
Poor



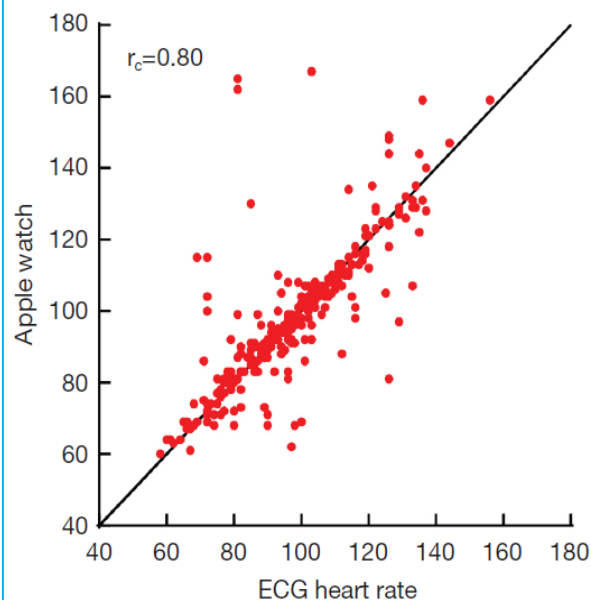
Accuracy
○ good
○ marginal
○ poor

Accuracy demands in wearable sensors

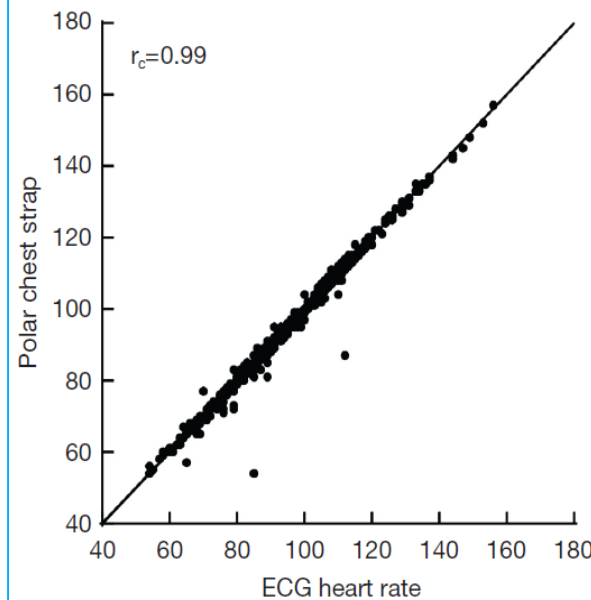
Garmin Forerunner 235



Apple Watch



Polar H7 chest strap



Value of high-performance sensors:

- Reliable detection of undesired conditions
- More convenient and effective screening and diagnosis
- More effective clinical research
- All – at cost-effective solutions

Etiwy et al., Accuracy of wearable heart rate monitors in cardiac rehabilitation, *Cardiovasc. Diagn. Ther.* **2019**, 9, 262-271

Accuracy demands in wearable sensors

More accurate readings without the goop

Y. Zhu, NC State Engineering FALL/WINTER, **2015**



<https://news.engr.ncsu.edu/2015/10/more-accurate-readings-without-the-goop/>

Silver nanowire wearable sensors match hospital 'wet electrode' accuracy

J. Ford, The Engineer, **2015**



<http://www.theengineer.co.uk/silver-nanowire-wearable-sensors-match-hospital-wet-electrode-accuracy/>

Forbes Billionaires Innovation Leadership Money Consumer

31,964 views | Sep 14, 2018, 01:15pm

Apple Watch 4 Is Now An FDA Class 2 Medical Device: Detects Falls, Irregular Heart Rhythm



2018

<https://www.forbes.com/sites/jeanbaptiste/2018/09/14/apple-watch-4-is-now-an-fda-class-2-medical-device-detects-falls-irregular-heart-rhythm/#3513aae82071>

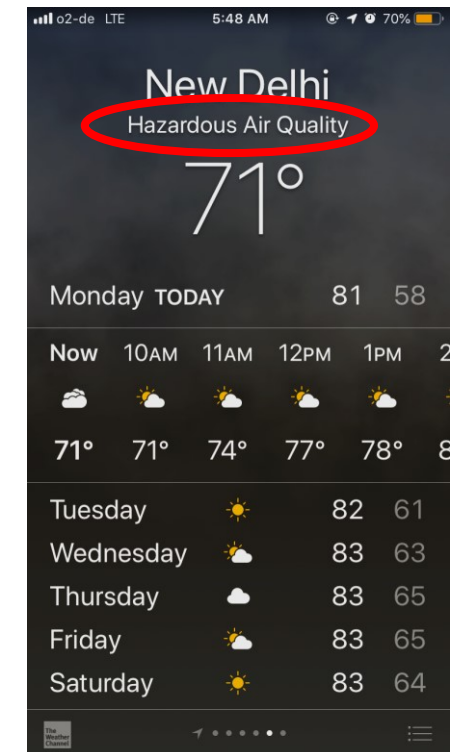
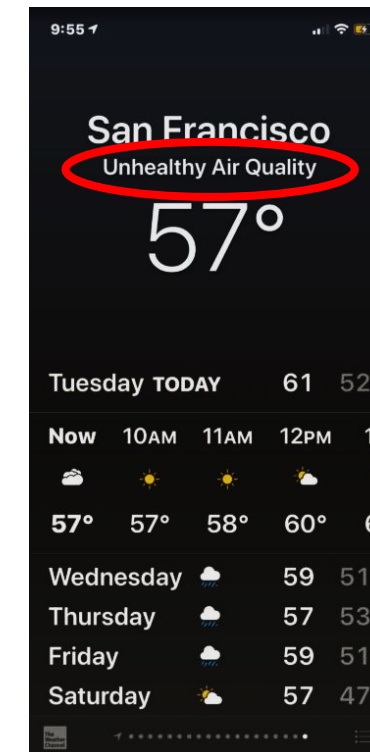
The wearable revolution took off because of the improved accuracy

Air quality index of ambient air: accepted metric

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health warnings of emergency conditions. The entire population is more likely to be affected.
Hazardous	301 to 500	Health alert: everyone may experience more serious health effects

Air Sensor Guidebook, EPA/600/R-14/159 June 2014 www.epa.gov/ord

Display of readings of other sensors



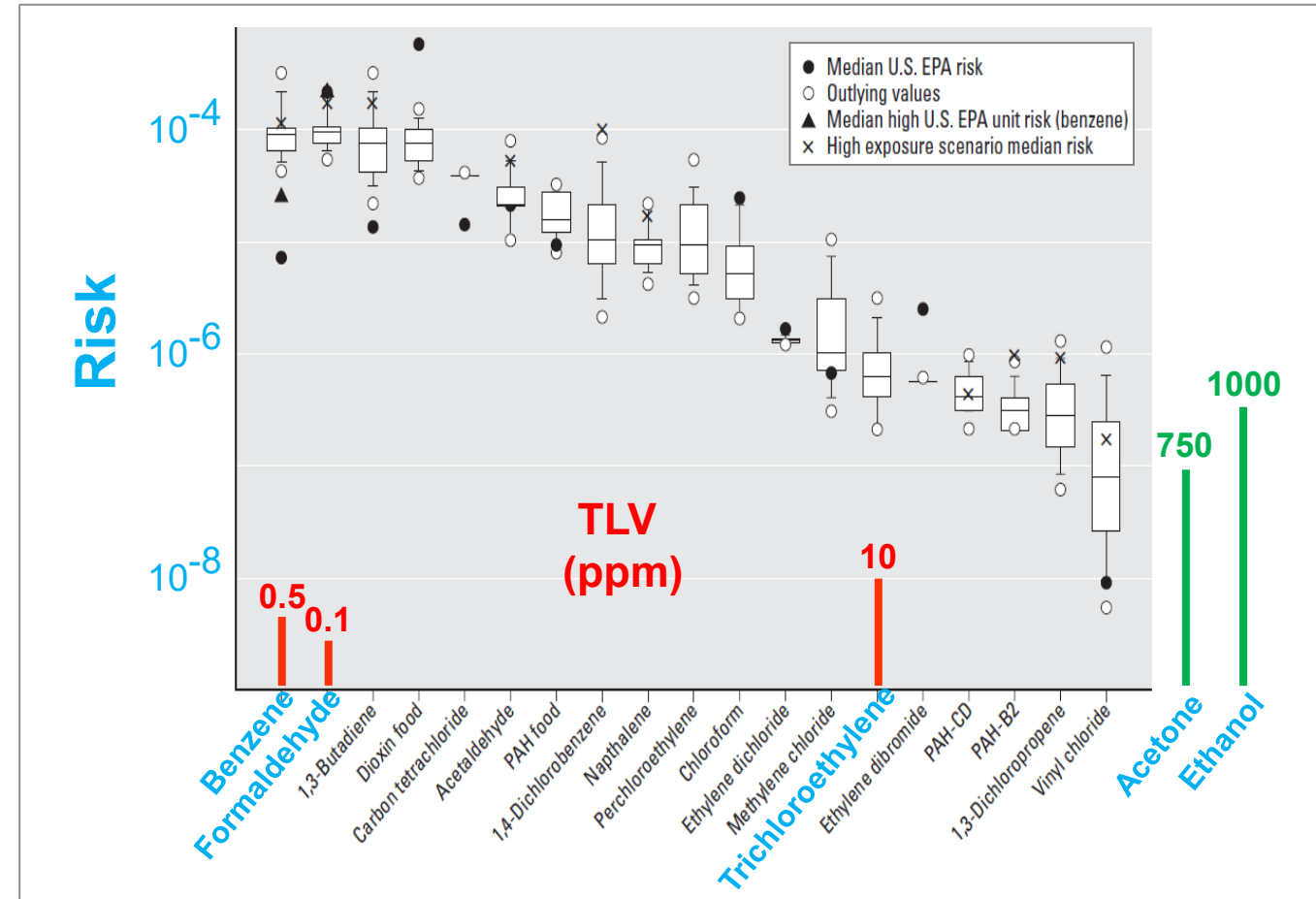
Important health-related volatiles: outdoor and indoor environments

Major outdoor volatile pollutants

Ozone < 0.1 ppm
 Nitrogen dioxide < 0.2 ppm
 Sulfur dioxide < 0.2 ppm
 Carbon monoxide < 30 ppm

Brunekreef, Holgate, *Lancet* **2002**, 360, 1233–1242
who.int/ceh/capacity/Outdoor_air_pollution.pdf
euro.who.int/document/e71922.pdf
who.int/airpollution/ambient/pollutants/en/

Indoor volatiles of importance



Risks from: Loh et al., *Environmental Health Perspectives*, **2007**, 115, 1160-1168

TLV (Threshold Limit Values) from: Permissible Exposure Limits / OSHA

- Some volatiles are much more toxic than others
- Toxic volatiles often are at much lower levels than benign volatiles
- Need to detect toxic volatiles in complex background of benign volatiles

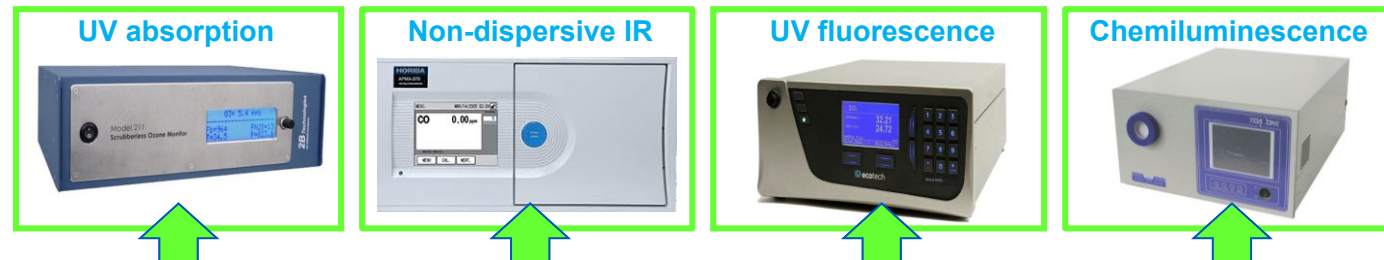
Air quality index: determined from measurements by high performance instruments

AQI	AQI
$I_{low} - I_{high}$	Category
0-50	Good
51-100	Moderate
101-150	Unhealthy for Sensitive Groups
151-200	Unhealthy
201-300	Very Unhealthy
301-400	Hazardous
401-500	

O ₃ (ppb)	CO (ppm)	SO ₂ (ppb)	NO ₂ (ppb)
$C_{low} - C_{high}$ (avg)	$C_{low} - C_{high}$ (avg)	$C_{low} - C_{high}$ (avg)	$C_{low} - C_{high}$ (avg)
-	0.0-4.4 (8-hr)	0-35 (1-hr)	0-53 (1-hr)
-	4.5-9.4 (8-hr)	36-75 (1-hr)	54-100 (1-hr)
125-164 (1-hr)	9.5-12.4 (8-hr)	76-185 (1-hr)	101-360 (1-hr)
165-204 (1-hr)	12.5-15.4 (8-hr)	186-304 (1-hr)	361-649 (1-hr)
205-404 (1-hr)	15.5-30.4 (8-hr)	305-604 (24-hr)	650-1249 (1-hr)
405-504 (1-hr)	30.5-40.4 (8-hr)	605-804 (24-hr)	1250-1649 (1-hr)
505-604 (1-hr)	40.5-50.4 (8-hr)	805-1004 (24-hr)	1650-2049 (1-hr)

Technical Assistance Document for the Reporting of Daily Air Quality – the Air Quality Index (AQI). US EPA Office of Air Quality Planning and Standards. EPA-454/B-09-001, 2009
Revised Air Quality Standards For Particle Pollution And Updates To The Air Quality Index (AQI). US EPA Office of Air Quality Planning and Standards. 2013

Reference and Equivalent Methods Used to Measure National Ambient Air Quality Standards (NAAQS) Criteria Air Pollutants – Vol. 1, EPA/600/R-16/139, 2016



Traditional analytical instruments are used for required high-quality measurements

Examples of field-deployed monitoring solutions



<https://blog.aclima.io>
<http://eis-me.com>
<https://uk-air.defra.gov.uk>

Design principles of high performance analytical instruments: Diverse designs to reject known and unknown interferences

Chemiluminescence *

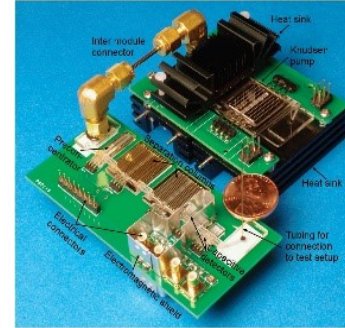


Reference and Equivalent Methods Used to Measure National Ambient Air Quality Standards (NAAQS) Criteria Air Pollutants – Vol. 1, EPA/600/R-16/139, 2016

UV fluorescence



Gas chromatography



Qin, Gianchandani, *Microsyst. Nanoeng.* 2016

Mass spectrometry

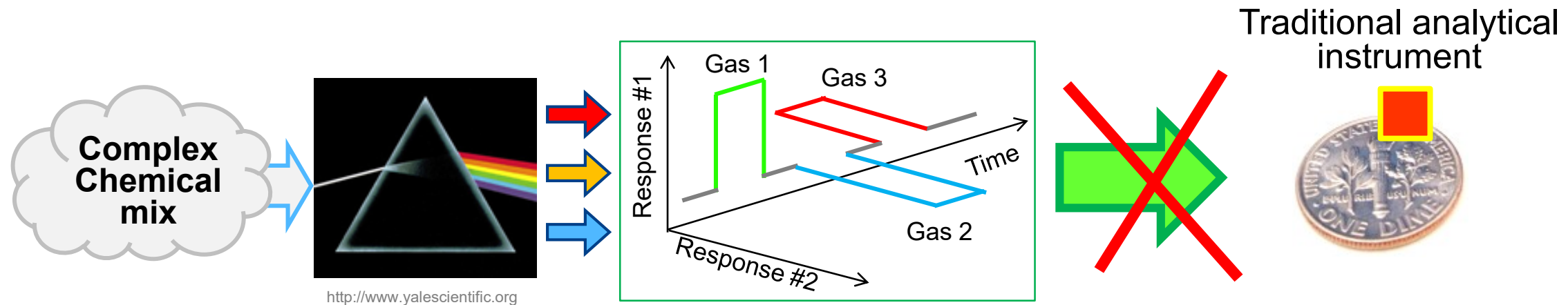


May 28, 2018

Laser spectroscopy



<https://alliedscientificpro.com>



Diverse instrument-design rules to operate in complex conditions

Current state-of-the-art in gas sensing

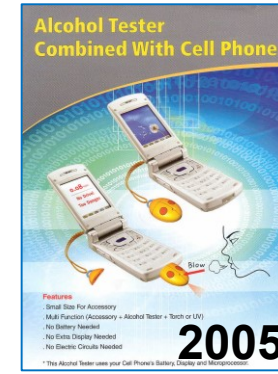


- ✓ Miniaturization
- ✓ Packaging
- ✓ Reduced power

Wearables

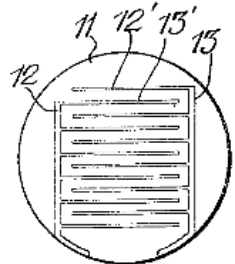


Cell phone integrated



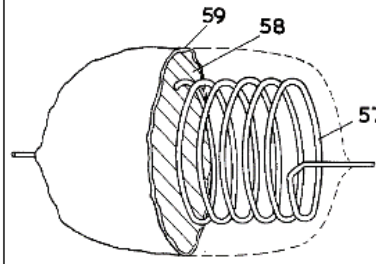
Conventional sensors: single-output devices for expected gases

Polymeric blends for humidity



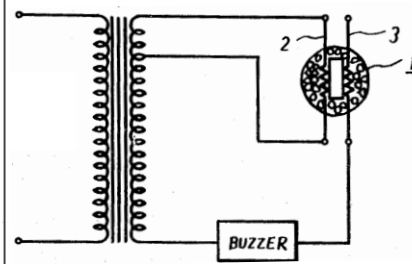
US Pat. 2047638, 1936

Catalysts for combustible gases



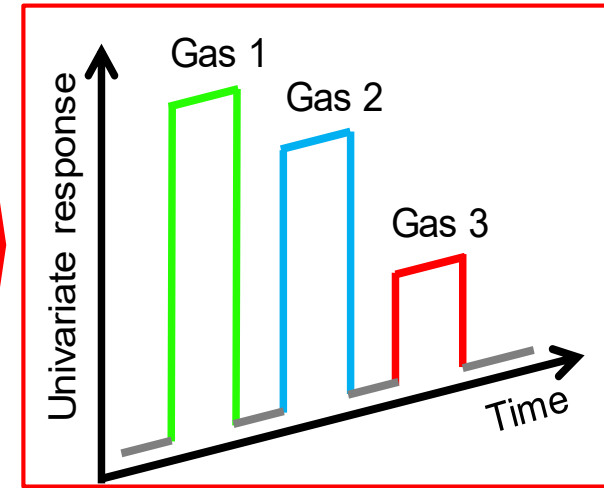
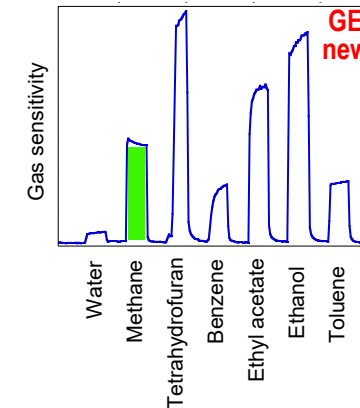
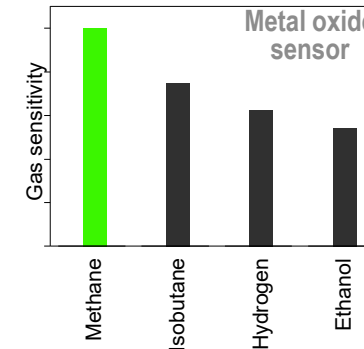
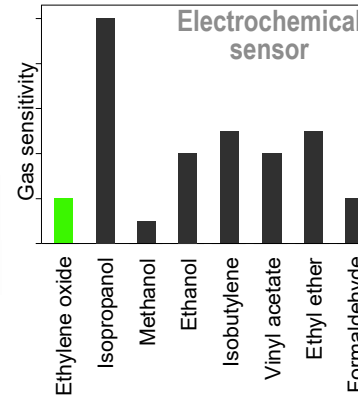
US Pat. 3092799, 1963

Metal oxides for diverse gases



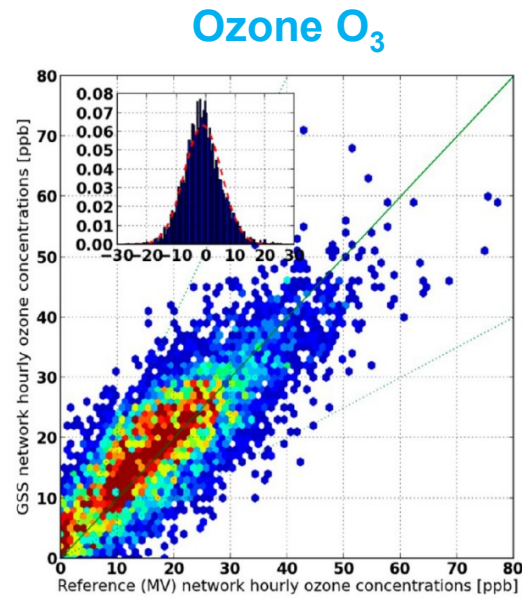
US Pat. 3644795 1972

Gas cross-sensitivity: undesired response to interfering gases

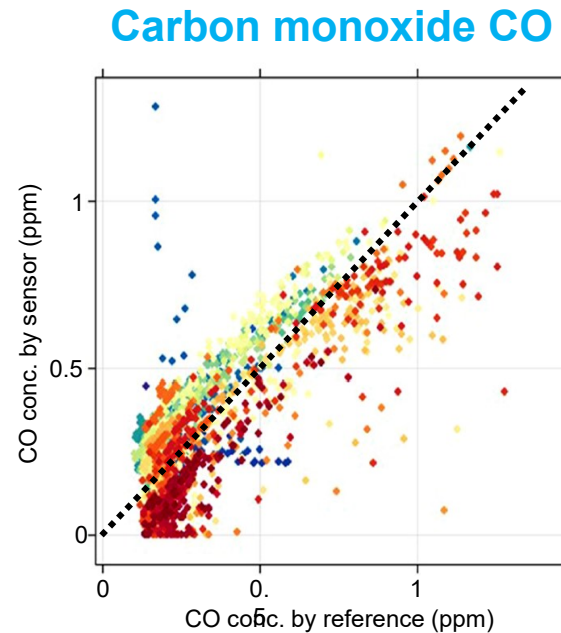


“Simple sensors perform best when pollution levels are high and when the compound of interest swamps others”
Lewis, Edwards, *Nature* 2016

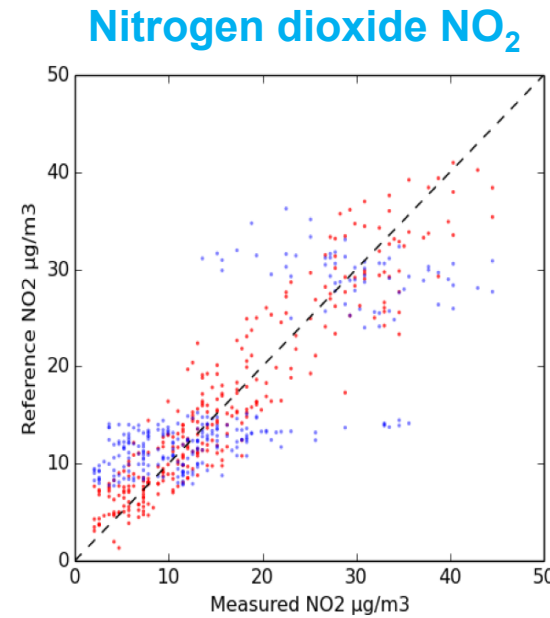
Examples + learnings: gas cross-sensitivity of existing sensors



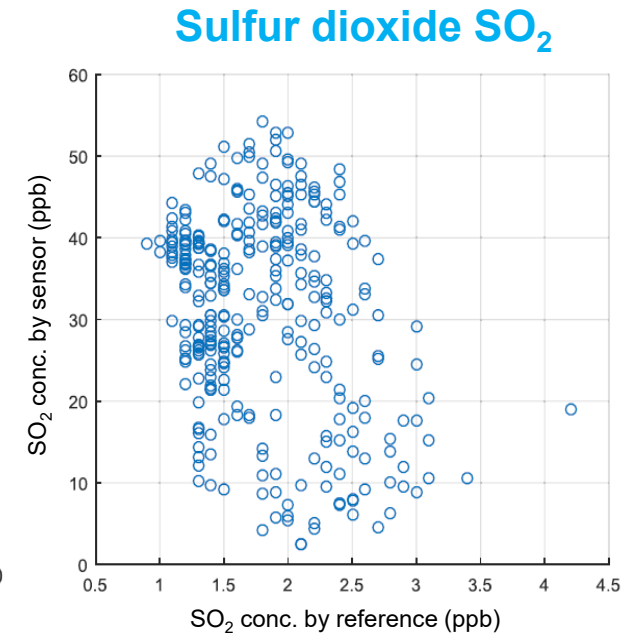
Bart et al., *Environ. Sci. Technol.* 2014, 48, 3970



Hagler et al., *Atmospheric Meas. Tech.* 2016, 9, 5281



Peterson et al., *Sensors* 2017, 17, 1653



Borrego et al., *Atmospheric Environment* 2016, 147, 246

The biggest headaches are caused by interfering chemicals
Lewis, Edwards, *Nature* 2016

ehstoday.com/sponsored/understanding-cross-sensitivities-can-help-keep-workers-safer



It must be stated that no low cost sensors meet the Regulatory Monitoring requirements

Air Sensor Guidebook, EPA/600/R-14/159 2014



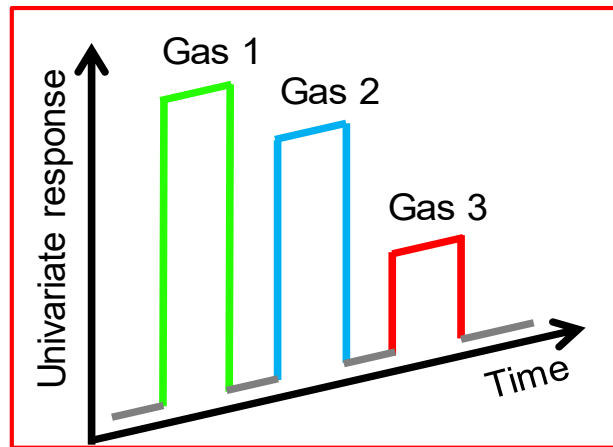
R^2 versus reference monitors widely variable (0.01 to ~ 0.8) in field evaluations

New Paradigm for Air Pollution Monitoring, Air and Energy Research Program, EPA 2018

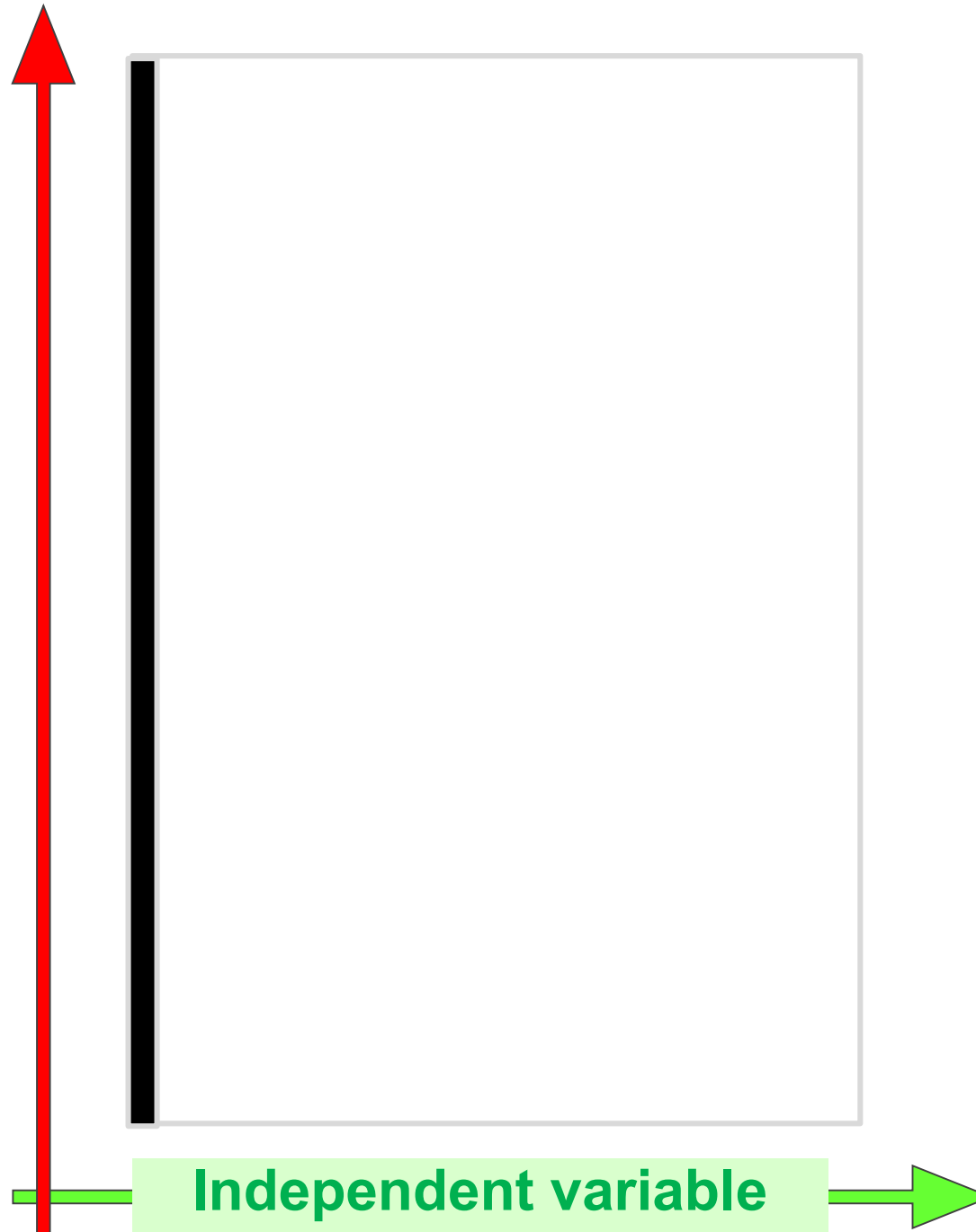
For gas sensors revolution to take off, accuracy must improve

GE Vision: Boosting dimensionality of sensor response

**Conventional
single-output sensor**

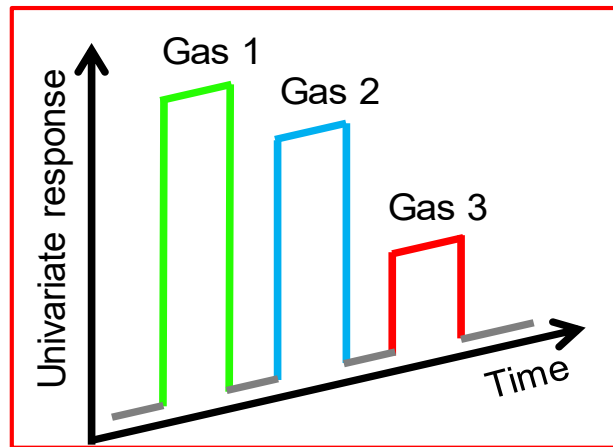


Single-output response

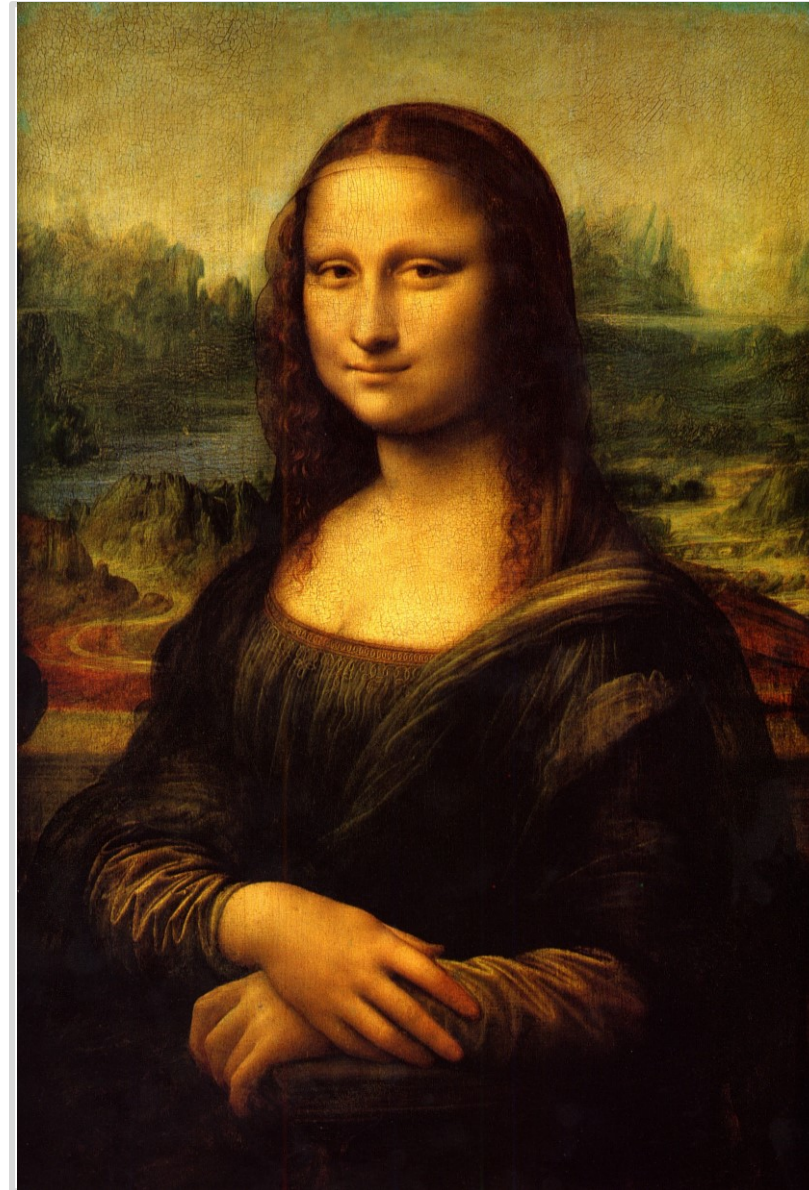


GE Vision: Boosting dimensionality of sensor response

Conventional single-output sensor



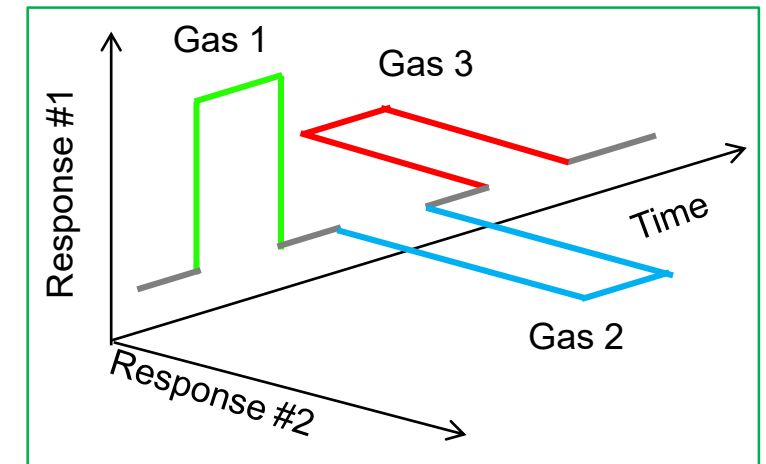
Single-output response



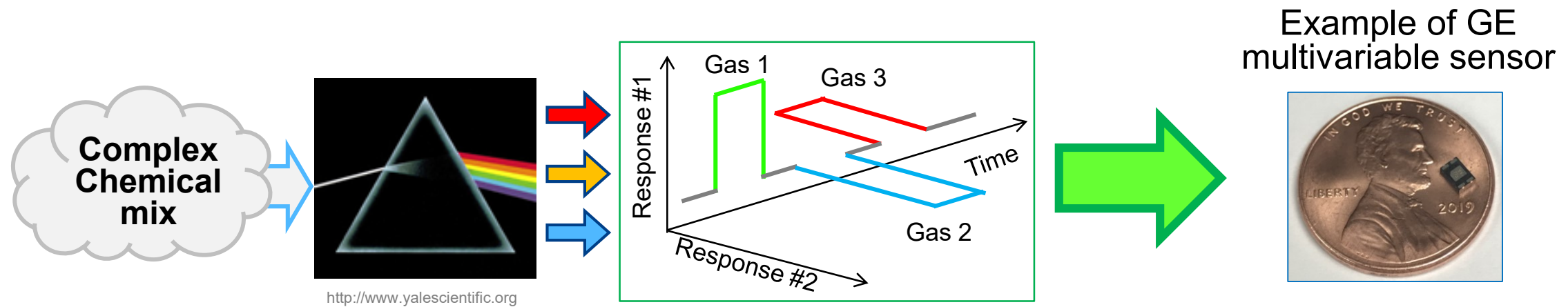
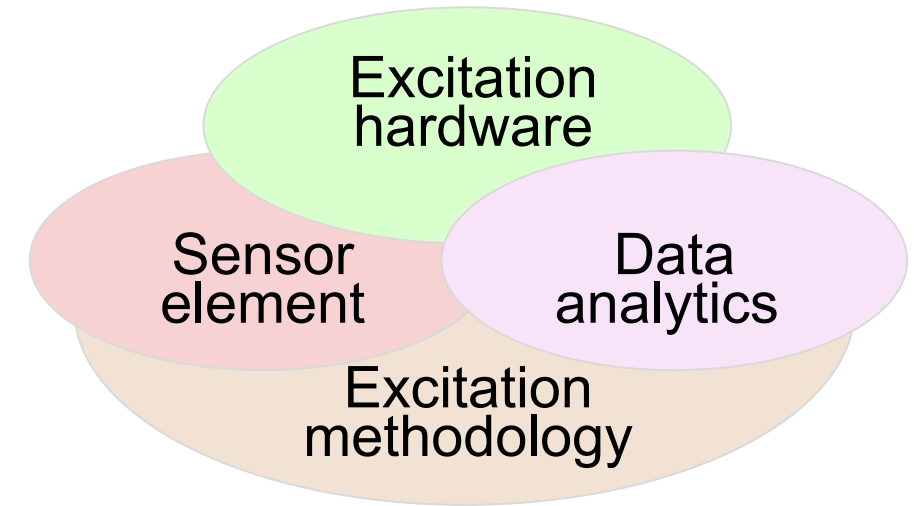
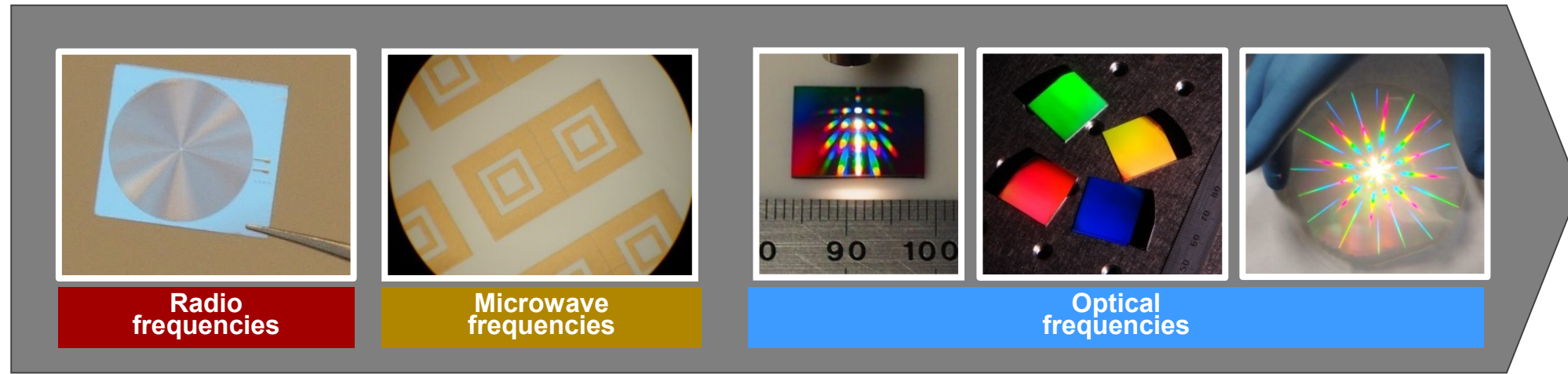
Independent variable

Types of independent variables

- Electrical modulation
- Optical modulation



Our roadmap: electromagnetic multivariable sensors



Present developments in gas sensing: Data analytics a.k.a. chemometrics, multivariate statistics, machine learning (ML)

Tools for diverse applications

Supervised learning

Artificial neural network
Bayesian statistics
Case-based reasoning
Gaussian process regression
Gene expression programming
Group method of data handling
Inductive logic programming
Instance-based learning
Lazy learning
Learning Automata
Learning Vector Quantization
Logistic Model Tree
Minimum message length
Probably approximately correct learning
Random Forests
Support vector machines
Symbolic machine learning

Unsupervised learning

Expectation-maximization algorithm
Vector Quantization
Generative topographic map
Information bottleneck method
Self-organizing map
Association rule learning
Hierarchical clustering
Single-linkage clustering
Conceptual clustering
Cluster analysis
K-means algorithm
Fuzzy clustering

Semi-supervised learning

Generative models
Low-density separation
Graph-based methods
Co-training

Wikipedia.org

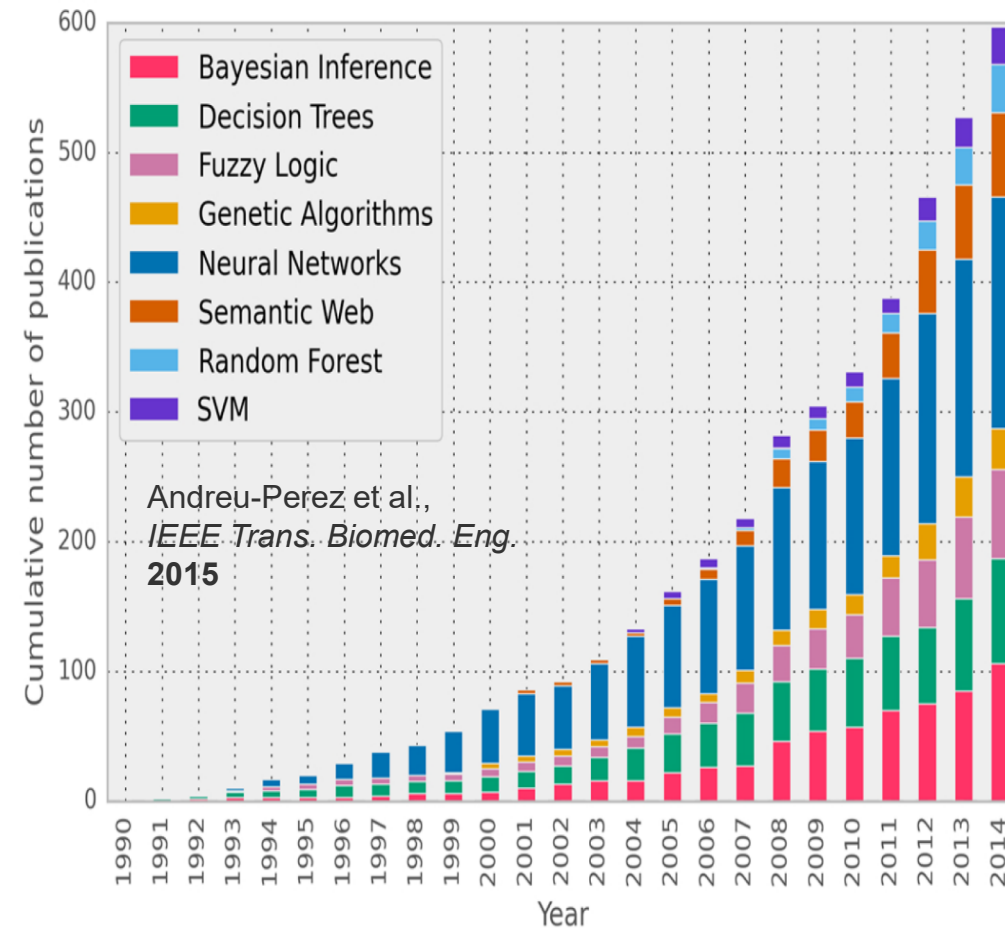
Reinforcement learning

Temporal difference learning
Q-learning
Learning Automata

Deep learning

Deep belief networks
Deep Boltzmann machines
Deep Convolutional neural networks
Deep Recurrent neural networks
Hierarchical temporal memory

Tools for sensor data processing



Examples of GE Research tools

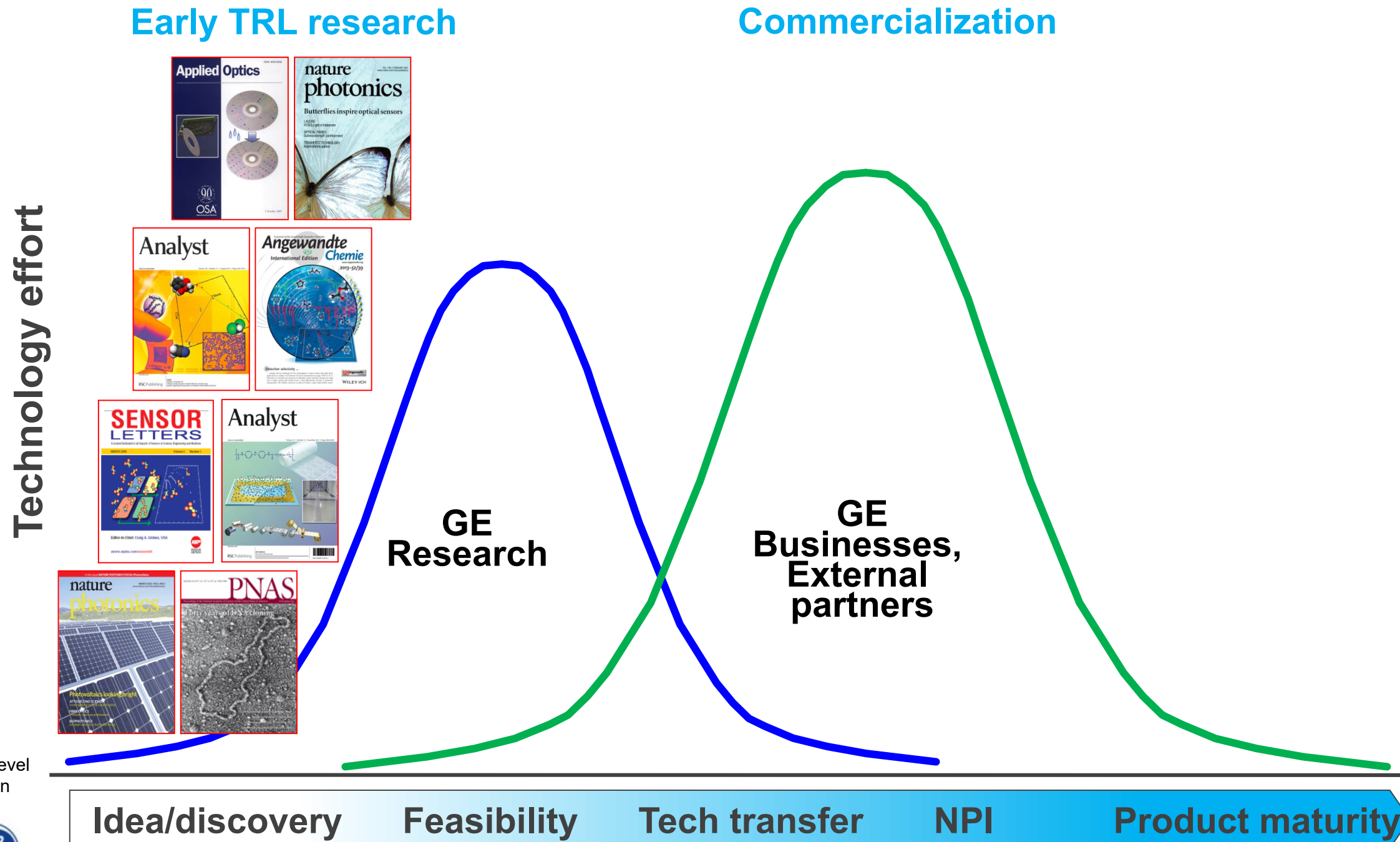
- Support Vector Machines (SVM)
- Principal component analysis (PCA)
- Hierarchical cluster analysis (HCA)
- Discriminant Analysis (DA)
- Artificial Neural Network (ANN)
- Independent Component Analysis (ICA)
- Partial least squares (PLS) regression
- Principal Component Regression (PCR)
- **New tools for boosting sensor stability**

R. A. Potyrailo, Multivariable sensors for ubiquitous monitoring of gases in the era of Internet of Things and Industrial Internet, *Chem. Rev.* 2016, 116, 11877–11923

Appropriate sensor + appropriate data analytics = high performance sensing

Our industrial R&D goal:

Develop technologies with new capabilities, transition for commercialization



Early TRL research

Commercialization

Technology effort

GE Research

GE Businesses, External partners

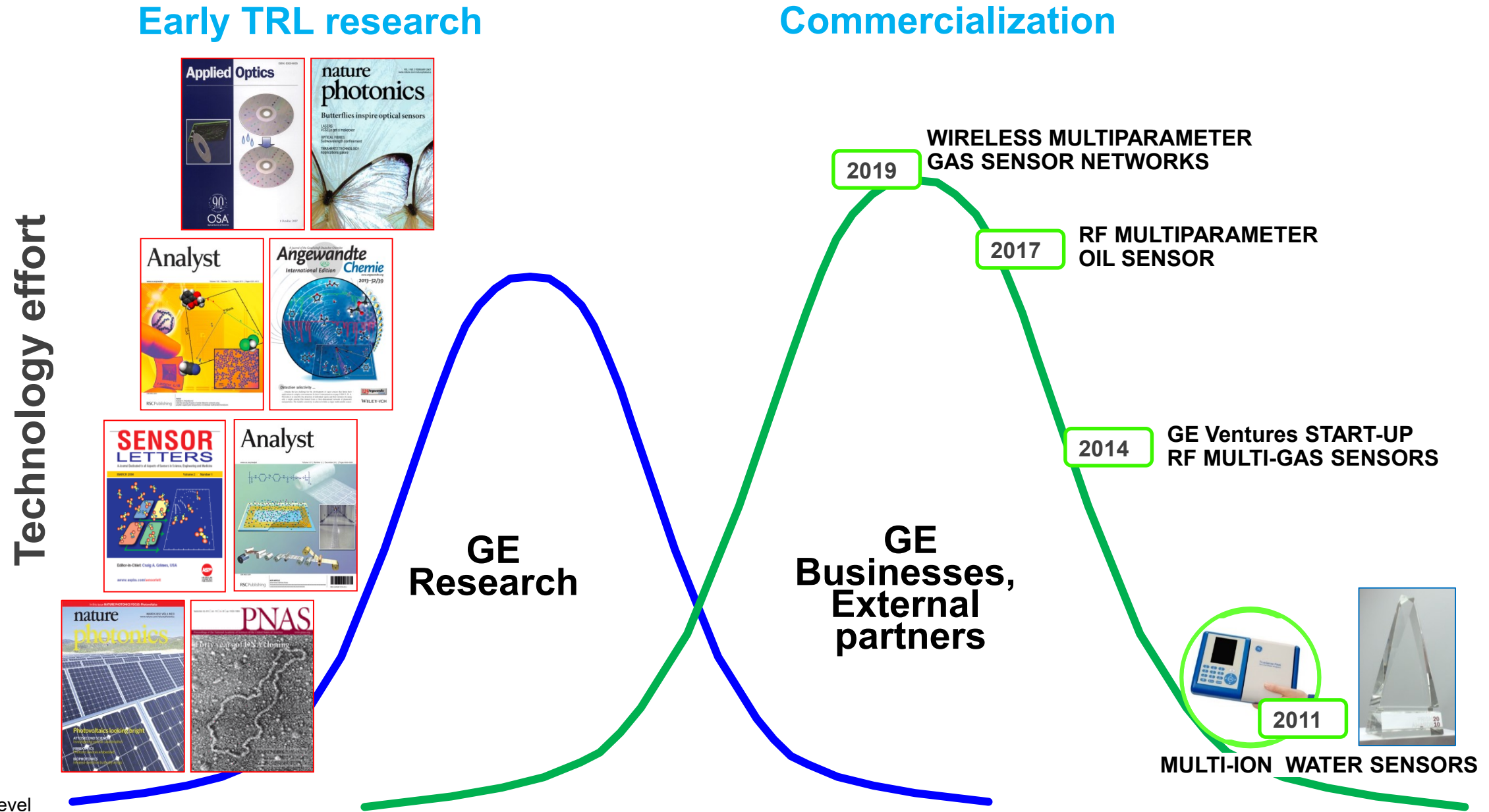
Idea/discovery Feasibility Tech transfer NPI Product maturity

TRL = technology readiness level
NPI = new product introduction



Our industrial R&D goal:

Develop technologies with new capabilities, transition for commercialization

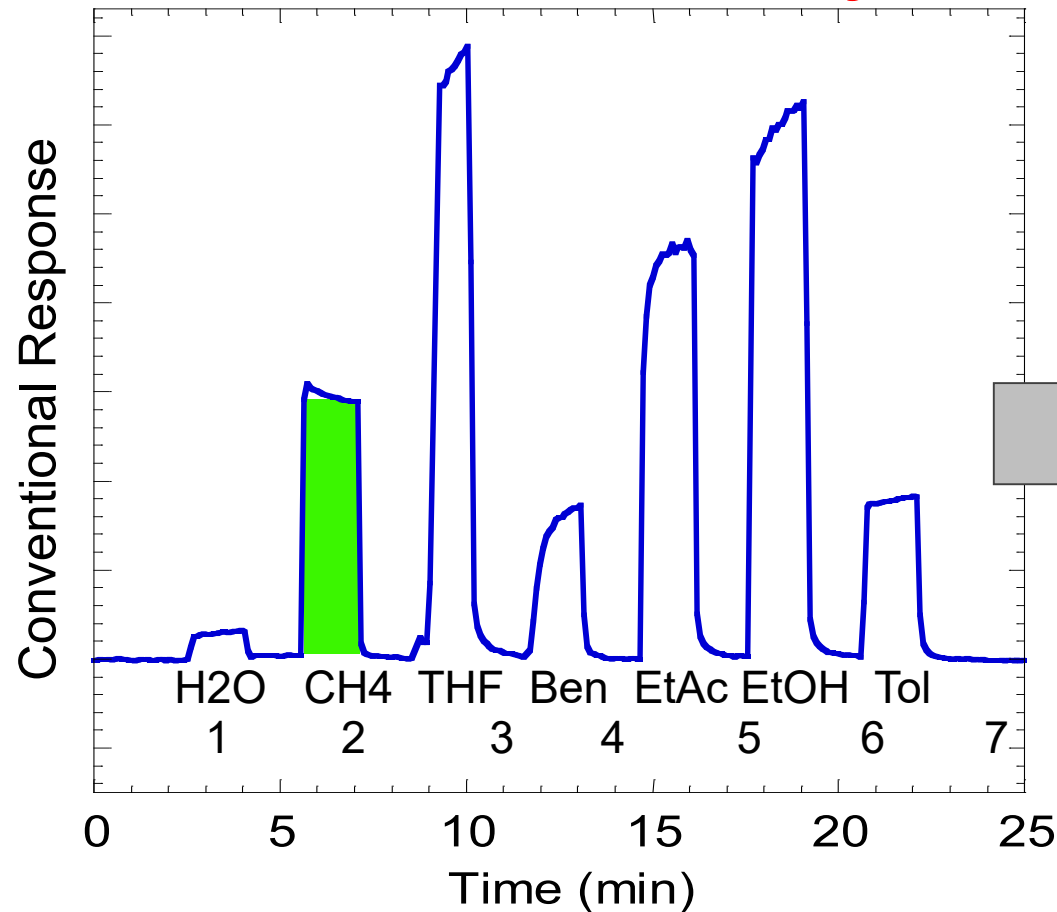


TRL = technology readiness level
NPI = new product introduction

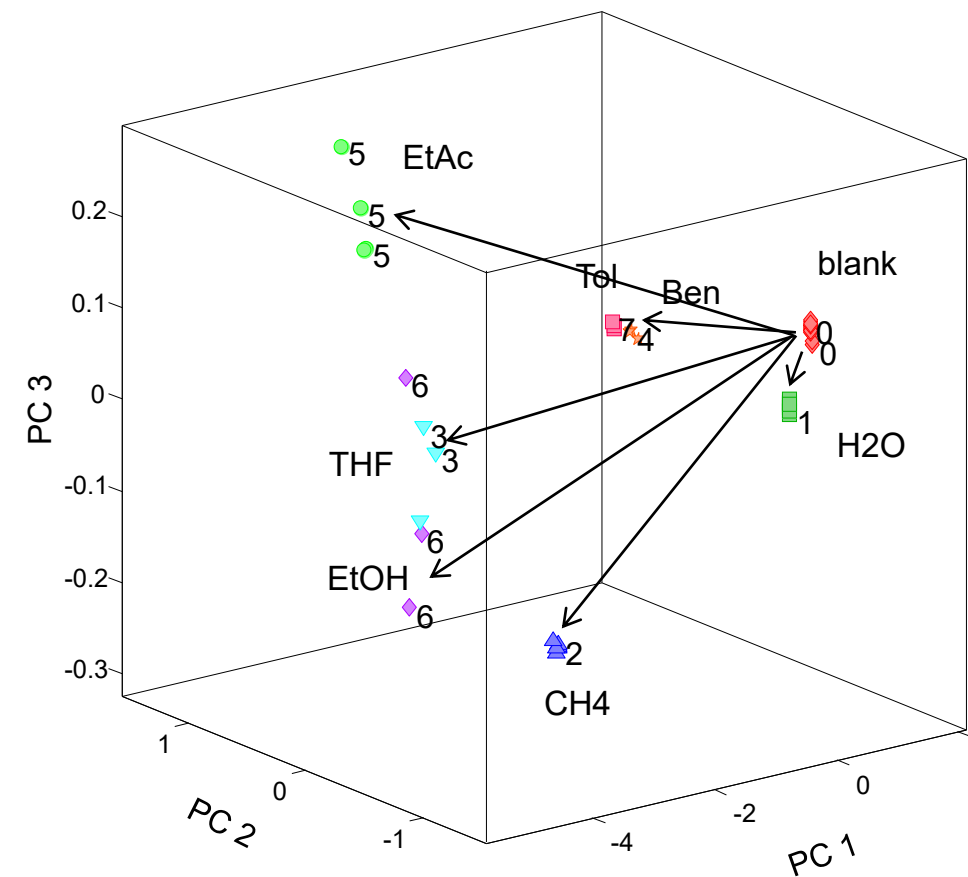


Discrimination between multiple gases and vapors

**Conventional response:
Gas cross-sensitivity**



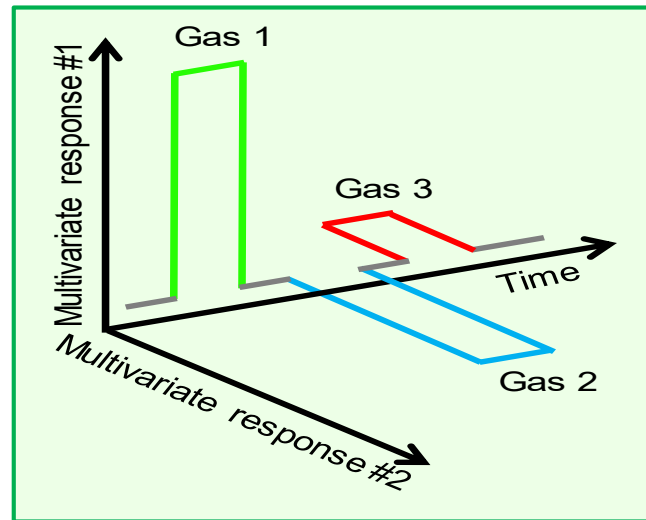
**GE response:
Multi-gas resolution**



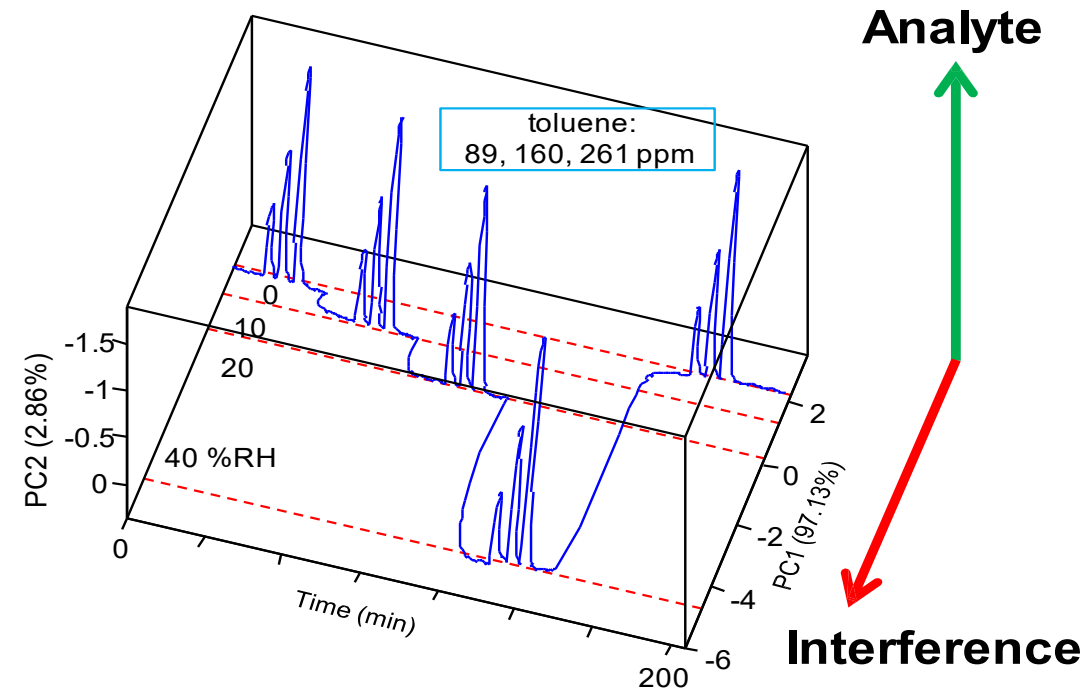
H2O = water
 CH4 = methane
 THF = tetrahydrofuran
 Ben = benzene
 EtAc = ethyl acetate
 EtOH = ethanol
 Tol = toluene

High performance sensing = appropriate sensor + appropriate data analytics

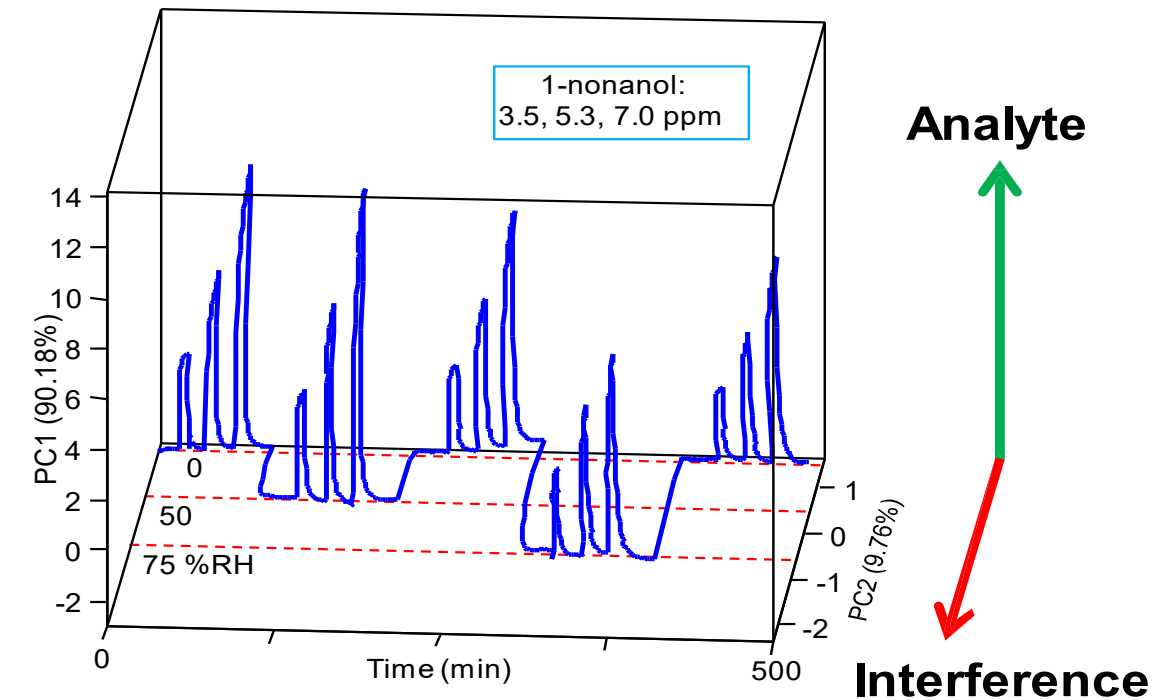
Interference rejection at 10,000 – 2,000,000 fold



10,000 fold rejection

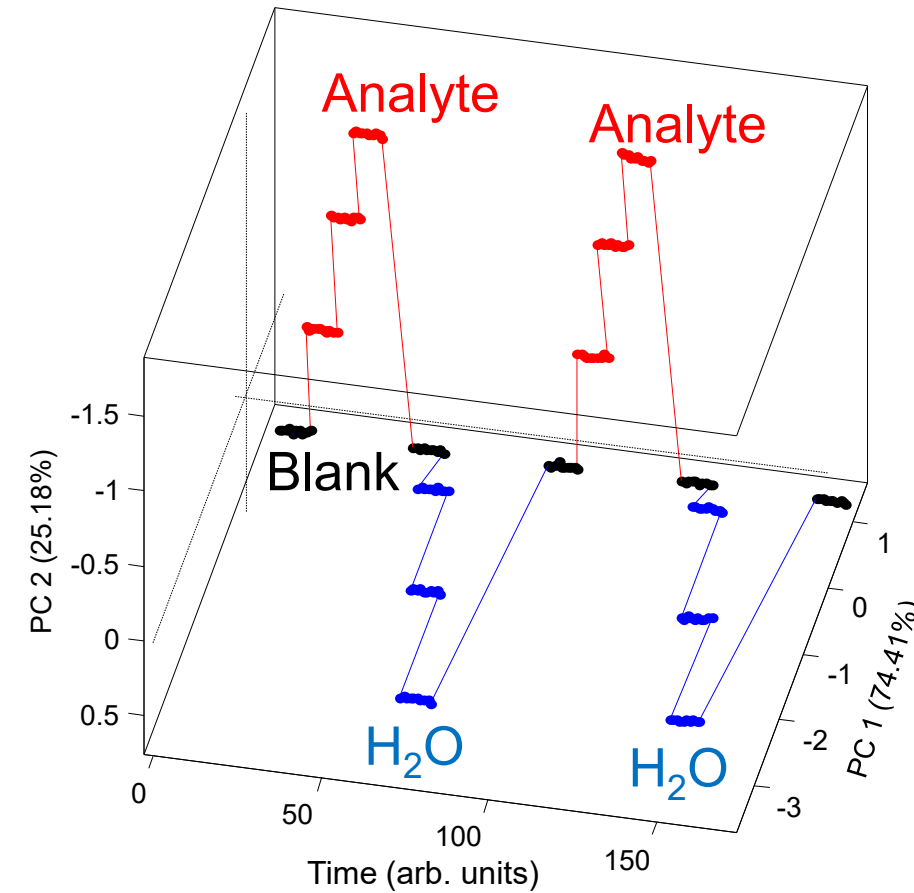
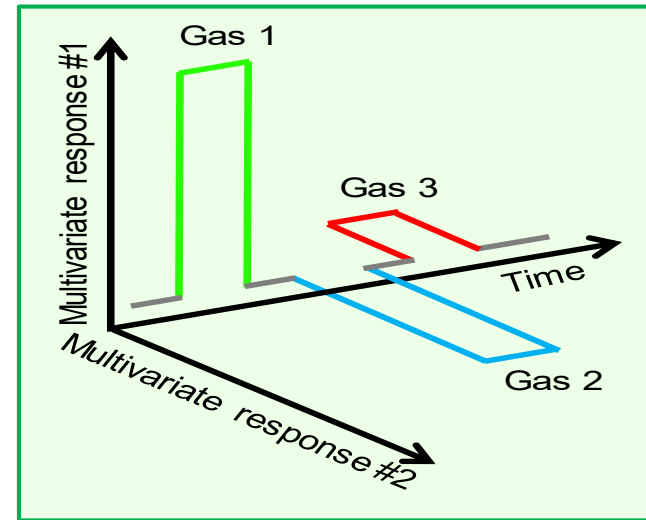
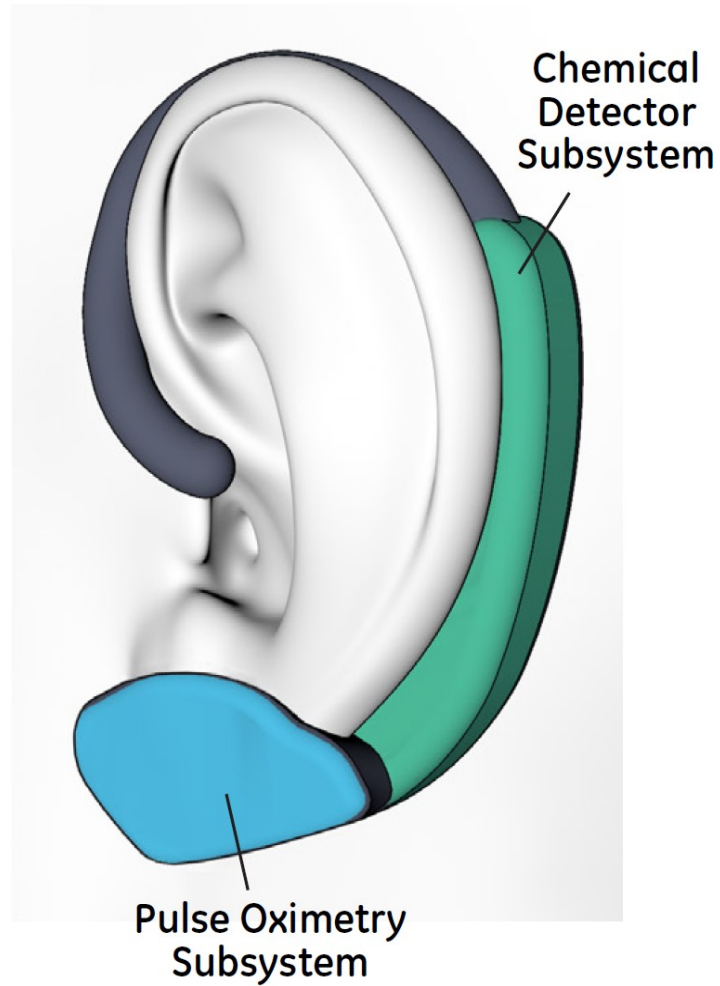


2,000,000 fold rejection



Immunity to interferences by applying new sensing philosophy

Wearable physiological sensor components for gas sensing



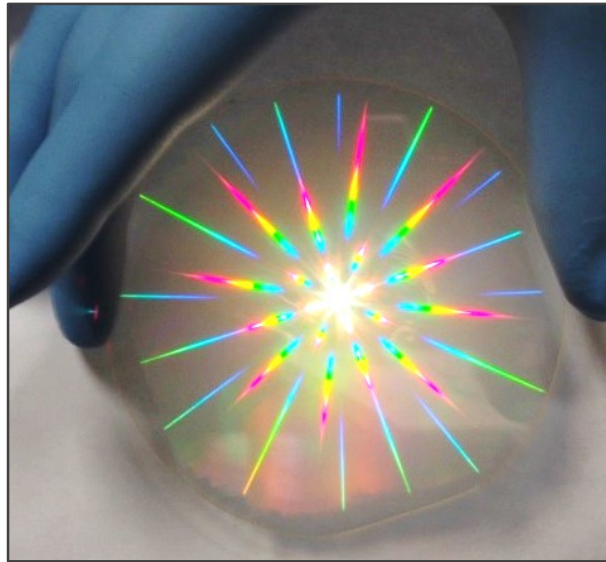
Analyte

Interference

Potyrailo et al, submitted to USPTO, 2019

Rejection of humidity on par with more bulky multivariable sensor systems

Single multivariable sensor outperforms sensor arrays



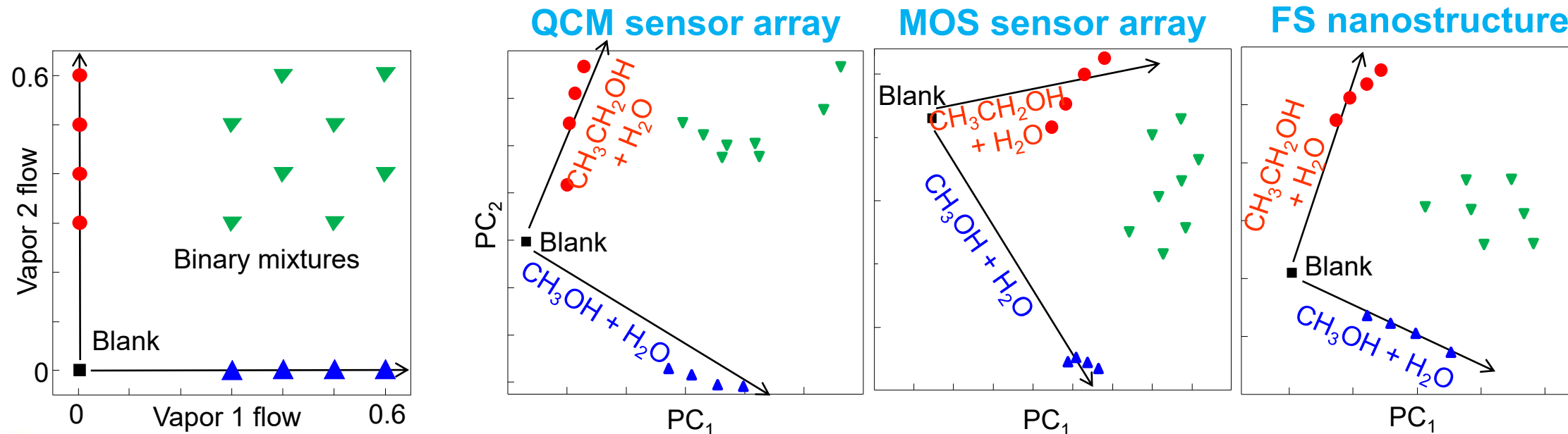
nature COMMUNICATIONS

ARTICLE

Received 22 Nov 2014 | Accepted 1 Jul 2015 | Published 1 Sep 2015 DOI: 10.1038/ncomms8959 **OPEN**

Towards outperforming conventional sensor arrays with fabricated individual photonic vapour sensors inspired by *Morpho* butterflies

Radislav A. Potyrailo¹, Ravi K. Bonam², John G. Hartley², Timothy A. Starkey³, Peter Vukusic³, Milana Vasudev^{4,5}, Timothy Bunning⁴, Rajesh R. Naik⁴, Zhexiong Tang¹, Manuel A. Palacios¹, Michael Larsen¹, Laurie A. Le Tarte¹, James C. Grande¹, Sheng Zhong¹ & Tao Deng^{1,6}



FS = nonafluorohexyl-trimethoxysilane
QCM = quartz crystal microbalance
MOS = metal oxide semiconductor

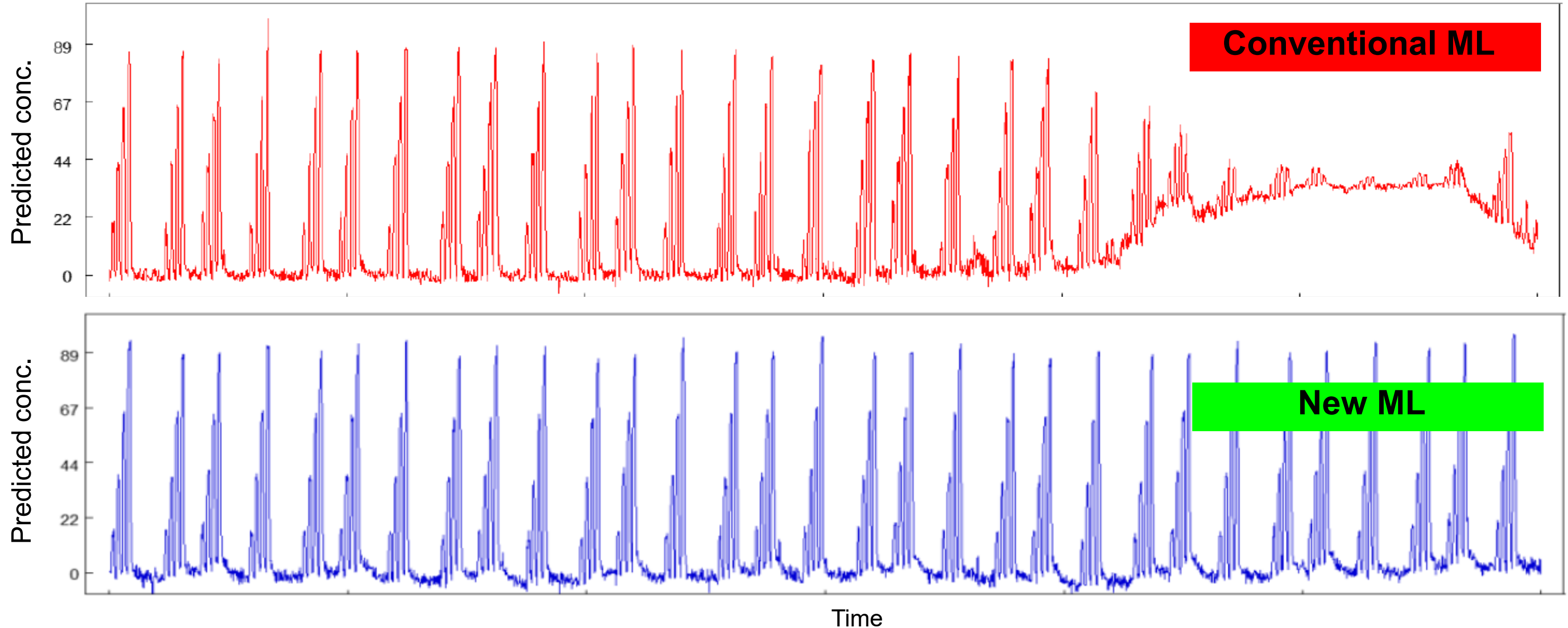
Potyrailo et al.
Nature Communications
2015

SEMICON EUROPA

12-15 NOV 2019

Radislav Potyrailo 2019 slide 25

Sensor stability boost: using new machine learning (ML) tools

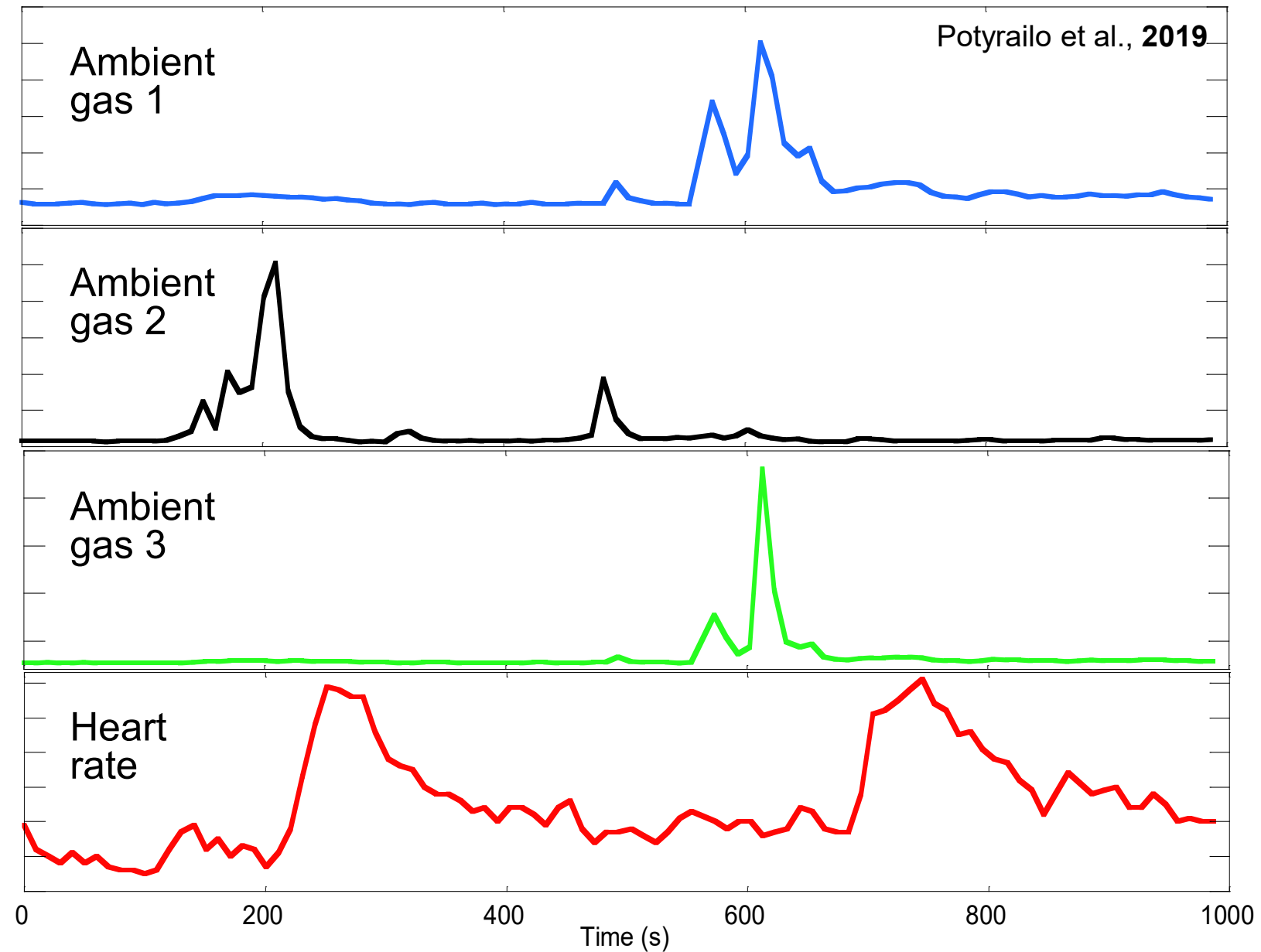


Classic vs GE ML to predict sensor response in the presence of drift

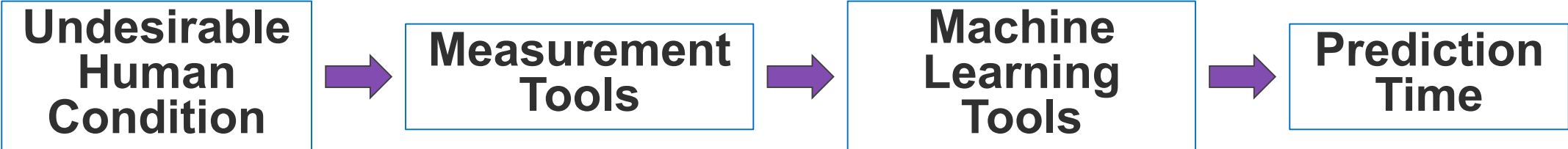
Fusion of high-performance gas and physiological sensors: new valuable capabilities



Graphic: GE Research



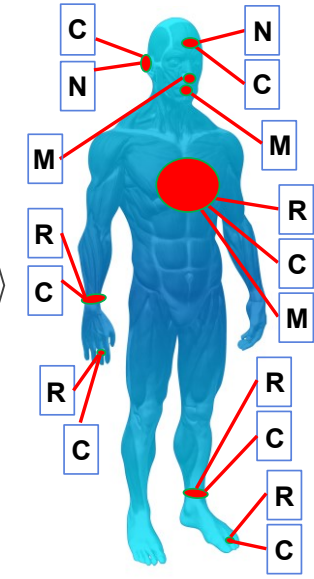
Toward prediction of undesirable human conditions



Physiological functions

- Neural (N)
- Respiratory (R)
- Circulatory (C)
- Metabolic (M)

Potyrailo , et.al., 2019



Graphic: GE Research

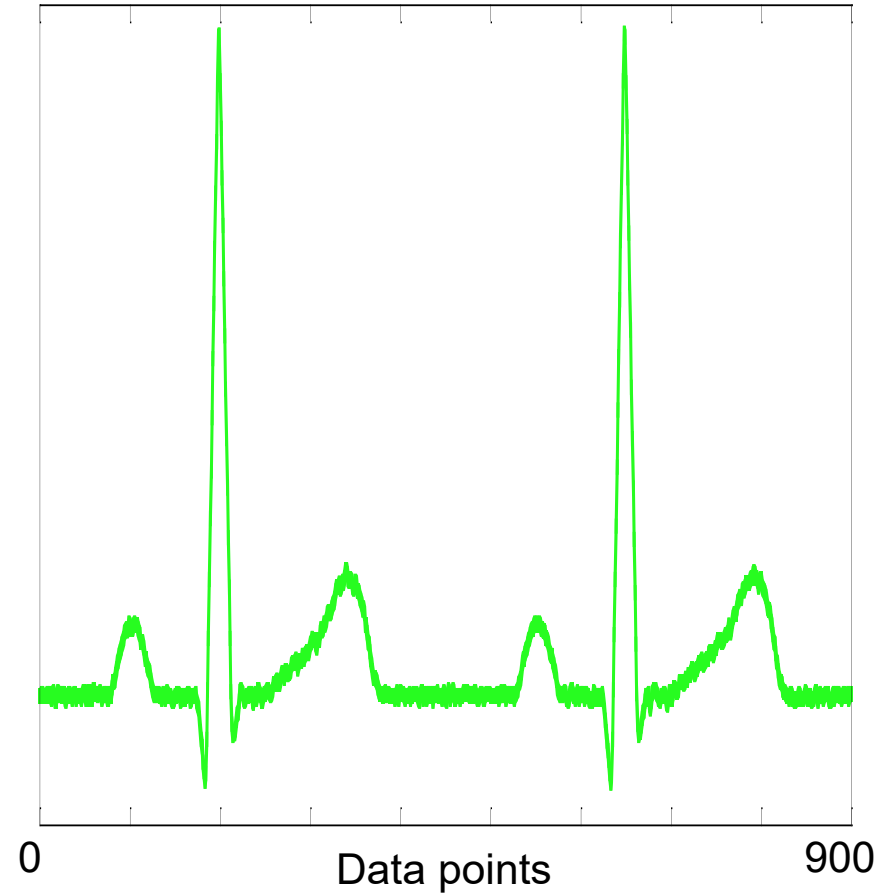
Diverse users of wearable sensors



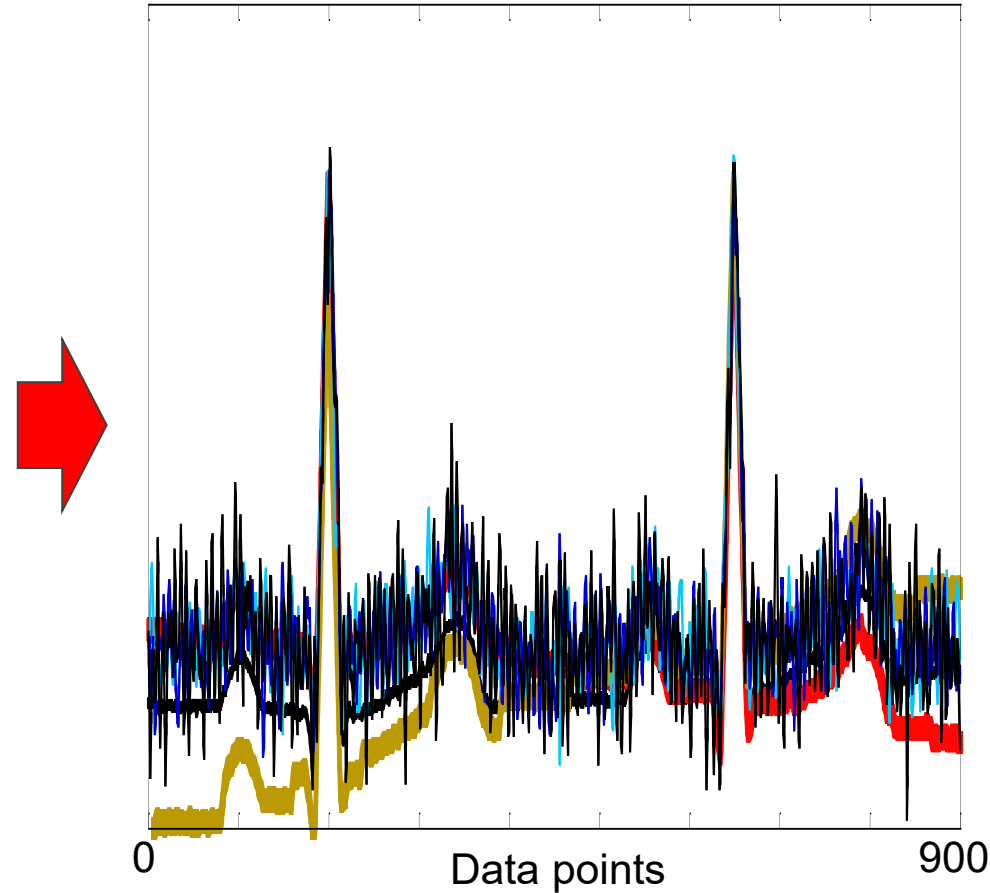
All graphics: GE Research

Simplifying hardware + system with preserved ECG data quality

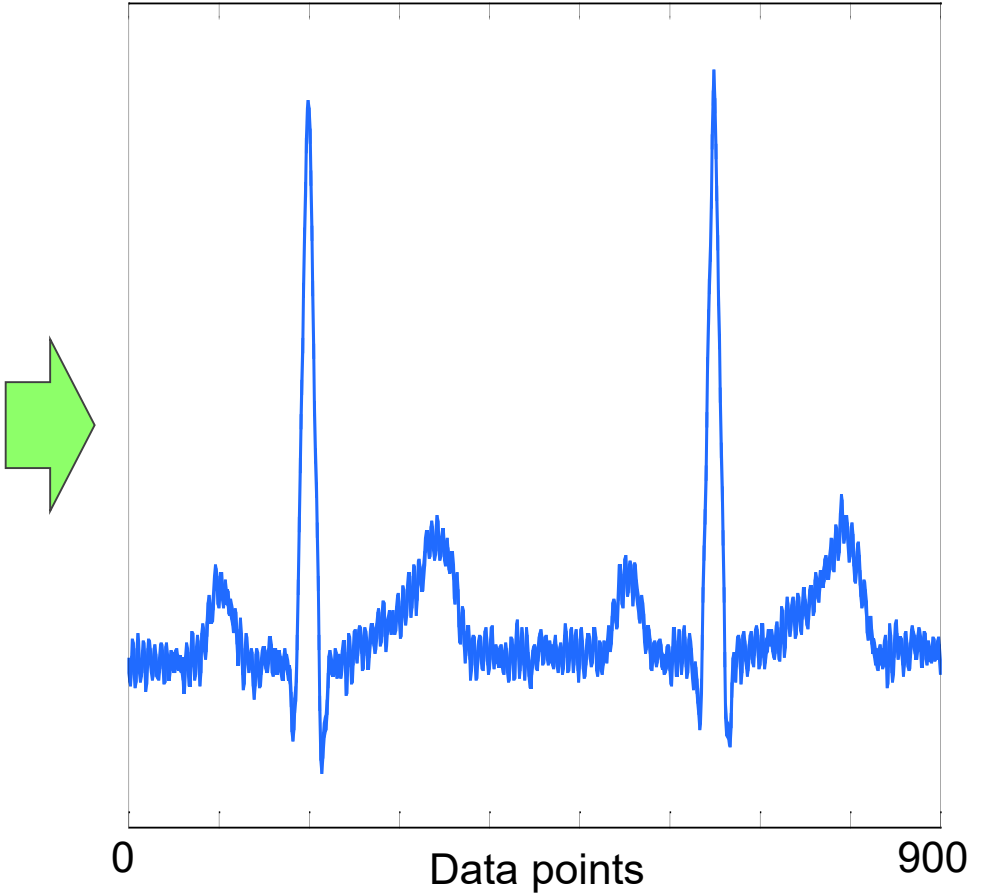
High quality (clinical)



With practical artifacts



Artifacts rejected



Rejection of poor electrode connection and electrode movements in ECG data

R. Potyrailo, A. Obi, 2019

Non-contact ECG signal processing and fusion

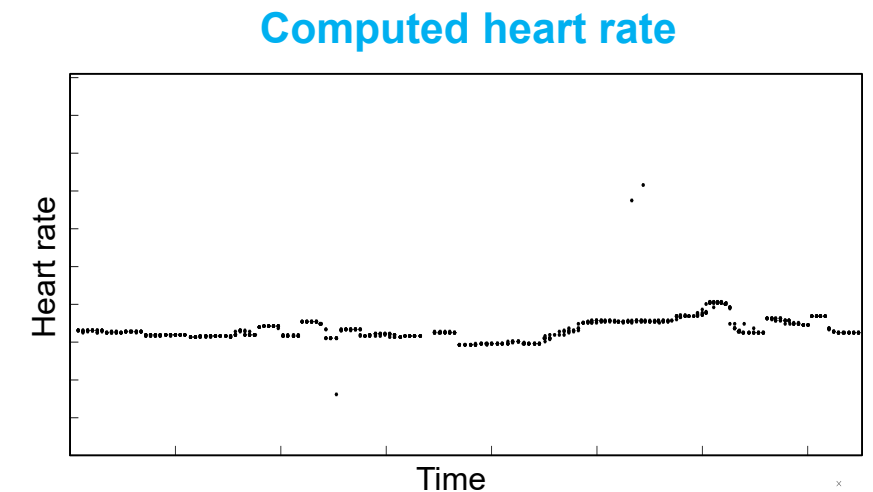
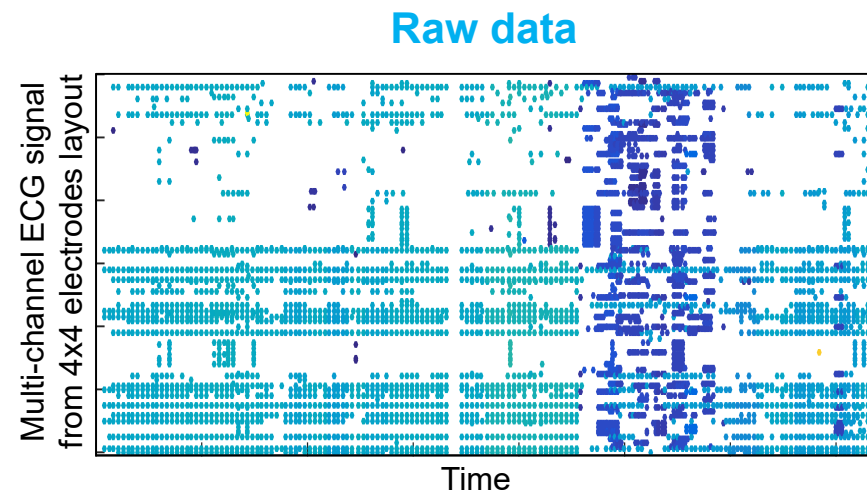
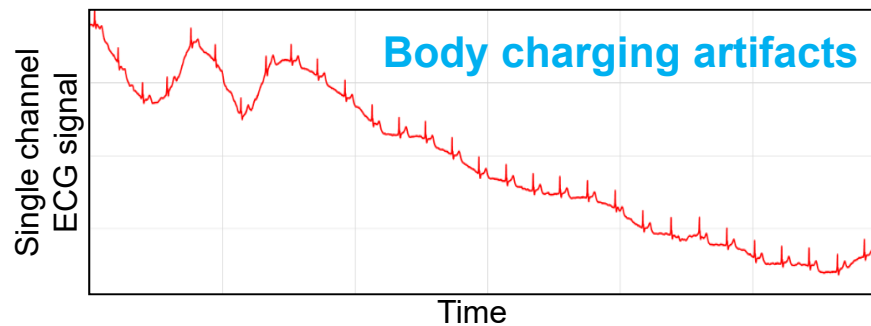
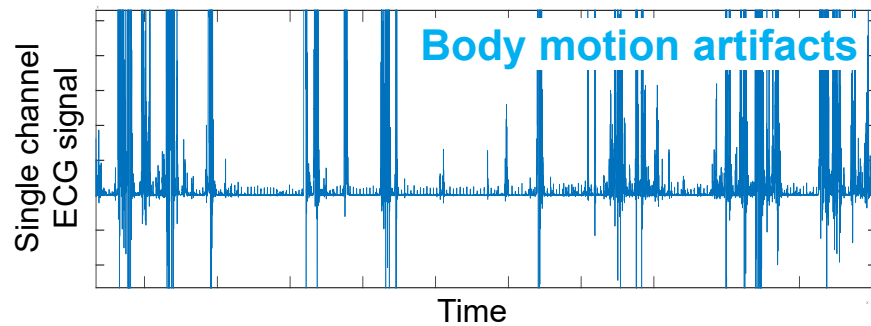


GE solutions for non-contact ECG

- Eliminated/reduced sensitivity to motion artifacts
- Signal recovery at next heart beat
- Clothing and subject robustness

Problems with non-contact ECG

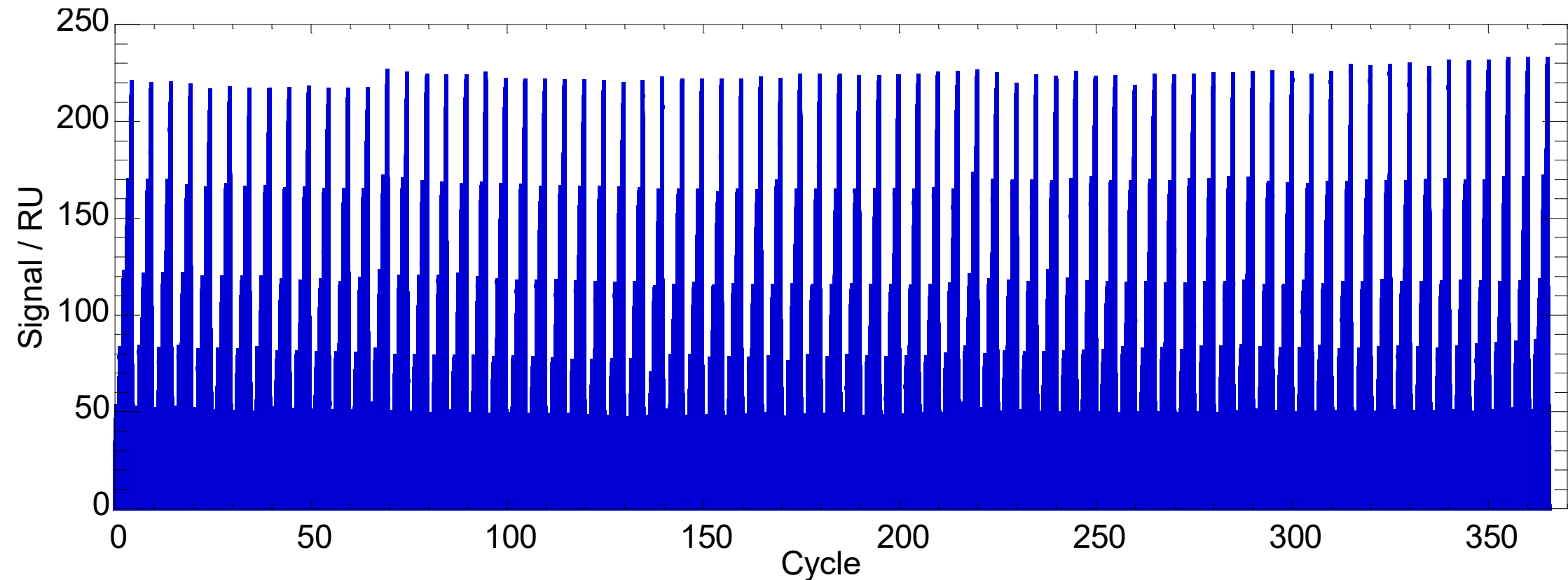
- Extreme sensitivity to motion artifacts
- 30 heart beat recovery time after signal loss
- Clothing and subject variability



Multi-electrode design + neuromorphic algorithm = high performance sensing

Reversible biorecognition for 365 bind/release cycles

Toward wearable reversible biosensing:



Highly stable binding affinity constant K_d over 365 bind/release cycles, $K_d = 2.5 \pm 0.1$ nM

Potyrailo et al. *Angew. Chem. Int. Ed.* 2015

Thrombin concentrations: 0.5, 1, 2, 4, and 8 nM
Substrate: Streptavidin Biacore chips
Chemical deactivation: 50 mM NaOH/1M NaCl

Future developments driven by multiple markets

Industrial Safety: \$3B

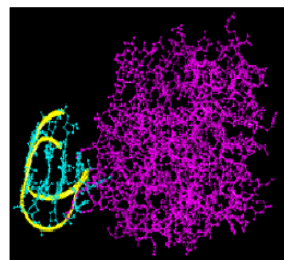
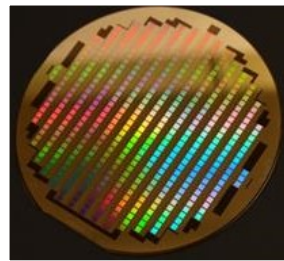
Health self-monitoring: \$15B

Wearable sensors: \$7B (2017) → \$24B (2023)

<https://www.marketsandmarkets.com/PressReleases/safety-instrumented-system.asp>

<https://www.prnewswire.com/news-releases/health-self-monitoring-technologies-and-global-markets-300102733.html>

<https://www.mordorintelligence.com/industry-reports/global-wearable-sensors-market>



Thank you !

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