### **IEEE SPMB 2020**

# **Artificial Intelligence for Clinical Trial Design**

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**IBM Research** 

December 5, 2020



# A (very) short history of Al **Cognitive Systems** Era Programmable Systems Era **Tabulating** Systems Era Big Data





# AI = <u>Augmented</u> (human) Intelligence

Brain-Machine Interface

Converse in spoken dialogue

**Comprehend text** 

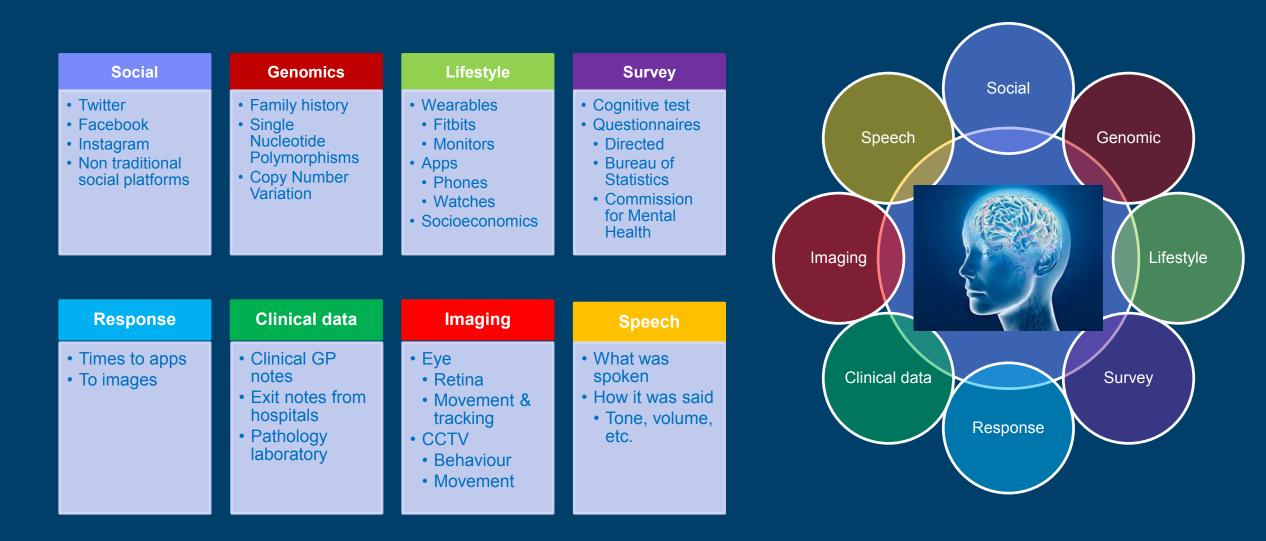
Comprehend complex images Analyse sensory data (for example: vision, hearing, touch, brain activity)

### Develop domain knowledge

### **Derive new insights**

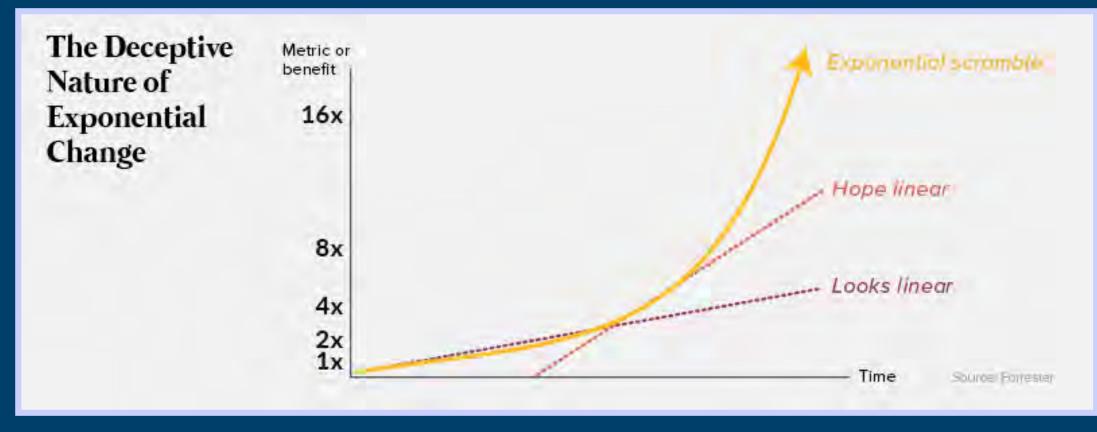


# Data is the new natural resource





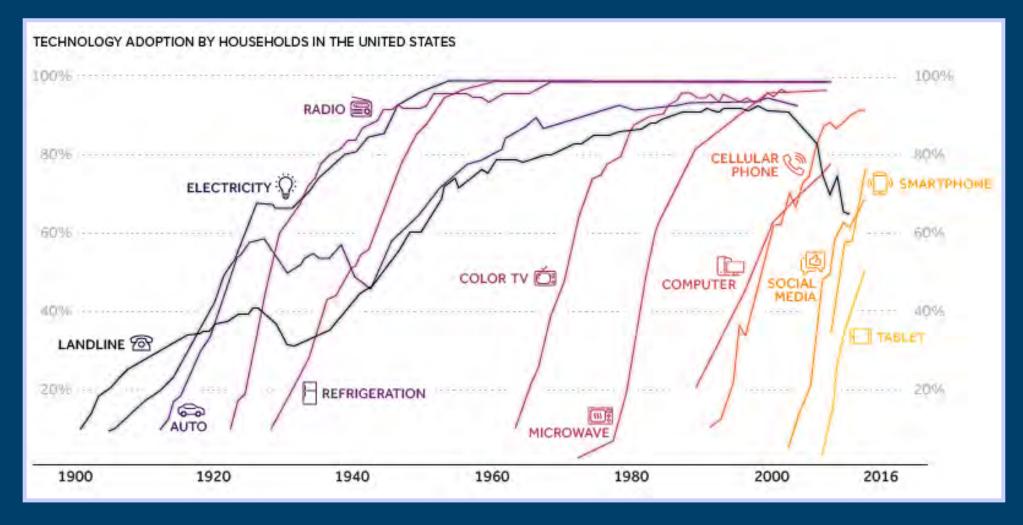
# The pace of technological progress – a human misconception



http://www.visualcapitalist.com/the-8-major-forces-shaping-the-future-of-the-global-economy/



# The future comes earlier these days than it used to...



http://www.visualcapitalist.com/the-8-major-forces-shaping-the-future-of-the-global-economy/



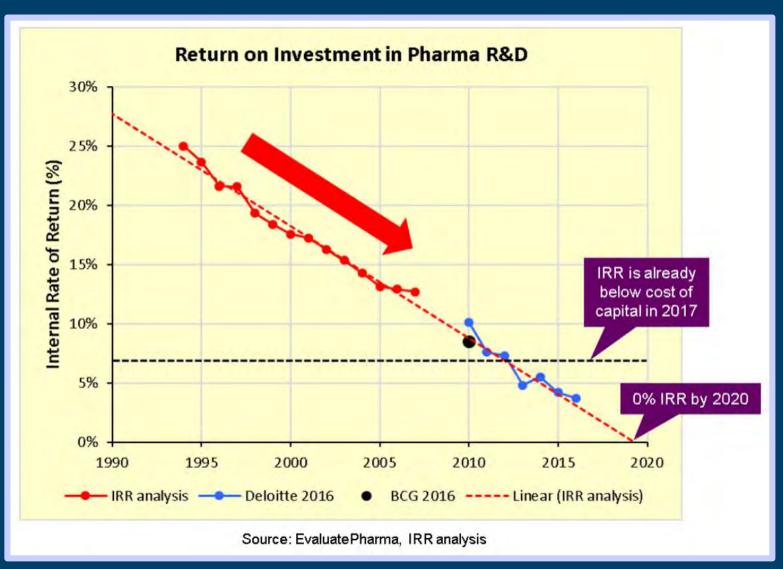
## Al must be used to assist the human decision maker





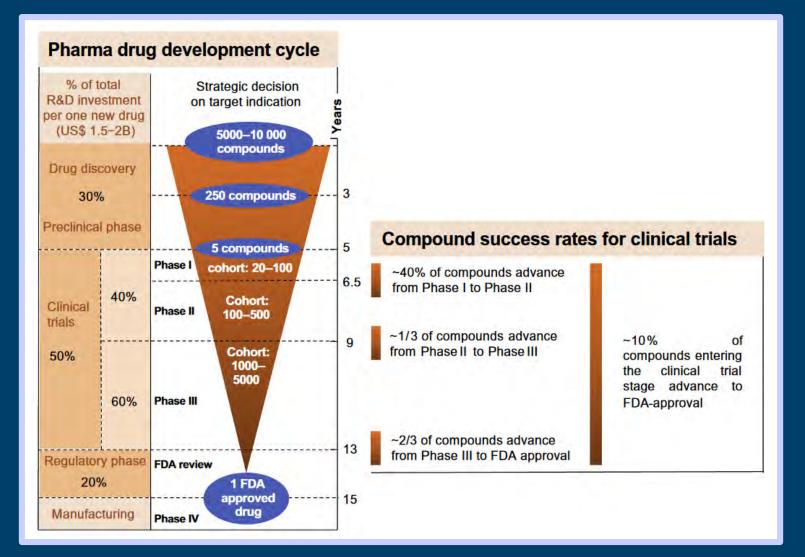


# The 'Pharma Dilemma'





# The Drug Development Cycle



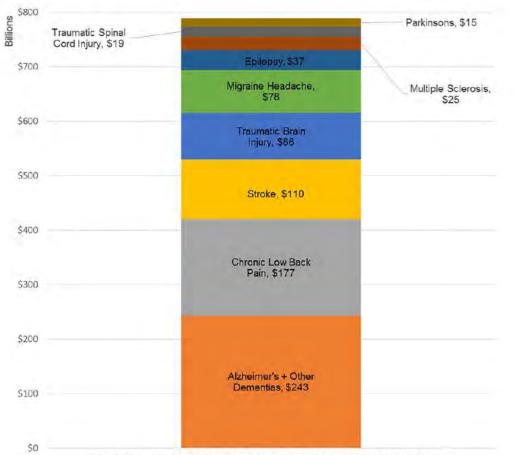
IBM

# Al for clinical trial design: from themes to functionality...

	Al techniques	Machine learning/Deep learning Reasoning Human–machi	ing/Deep learning ine interfaces	Machine learning/Deep learni Human–machine interfaces	ng Machine learning/Deep learning Reasoning Human–machine interfaces
	Data	EMR Omics Medical literature Clinical trial da Clinical domain knowledge Medical literatu Eligibility datal	ements Social media ure EMR	Internet of things ar	nd wearables Speech Video
	Outcomes	Optimized cohort composition		d chances ssful outcome	Lower dropout rates
		More effective trial planning and faster to launch	Faster an expensive		Improved patient adherence
		Challenges 1. EMR data harmonization (EM	IR interoperability pro	blem). 2. Data privacy, integri	ty, and security. 3. Explainability of Al



# Neurological diseases: burden on healthcare system



Yearly Economic Burden of Major Neurological Diseases in Billions (2014 Dollars)

FIGURE: Annual costs of major neurological diseases. Costs of Alzheimer disease and other dementias, chronic low back pain, stroke, traumatic brain injury, migraine headache, epilepsy, multiple sclerosis, spinal cord injury, and Parkinson disease. Dollar figures were converted into 2014 values using the all items consumer price index for nonmedical (indirect) costs. Direct costs were converted using the medical price index.



Invited Editorial

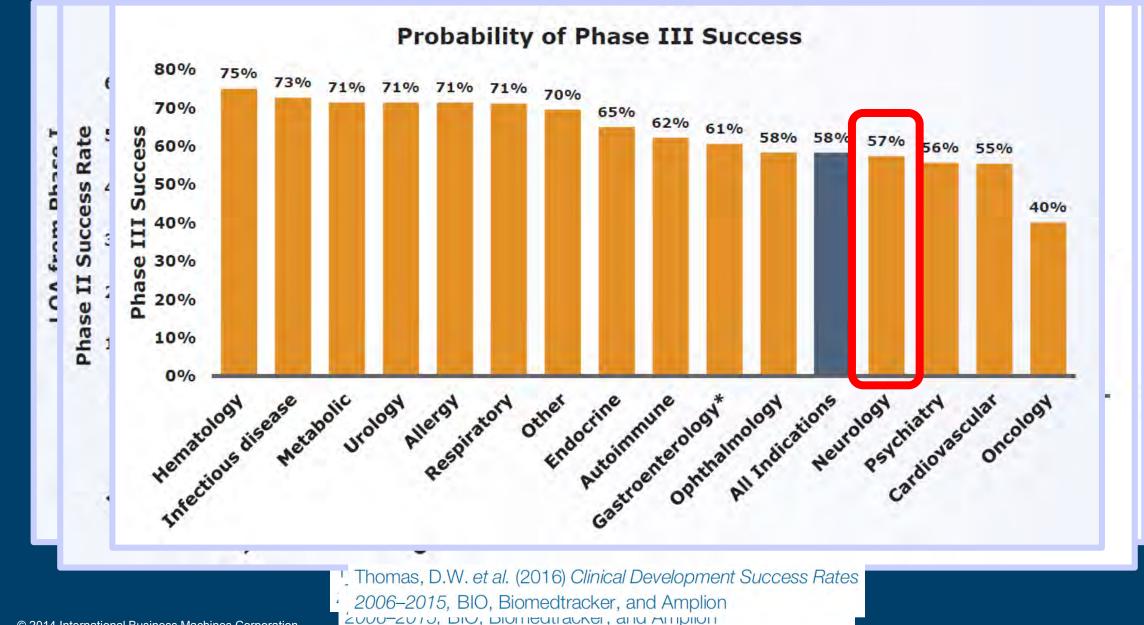
The burden of neurological disease in the United States: A summary report and call to action

Clifton L. Gooch MD, Etienne Pracht PhD, Amy R. Borenstein PhD



**#PharmSci360** 





# **Epilepsy: Patient Monitoring Using AI**

Epileptic seizures are electro-chemical signalling disturbances in the brain.

~1% 65M chronic epilepsy

> 65% treated with varying degrees of success

> > 35%

drug

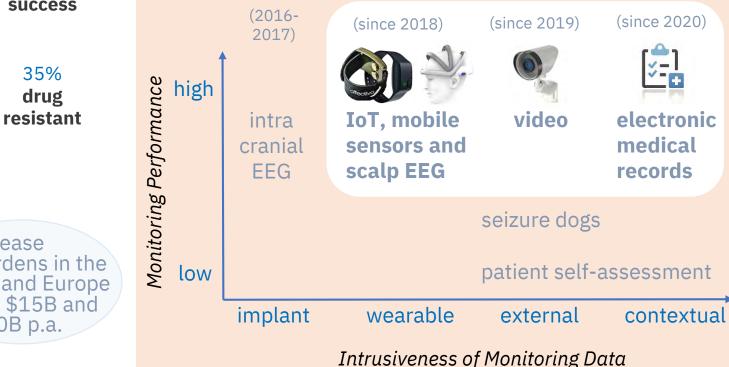
•



### **Automatically Detecting and Classifying Seizures**

- Patients are often unaware of their seizures. •
- Patients keep **diaries** but these are vastly inaccurate.
- Drugs are tested against diaries.
- Accurate seizure counts allow better treatment evaluation.

### **Digital Seizure Diaries: Automatic Seizure Tracking**



## IBM Research

We combine **deep learning**, **mobile sensors** and **video** data to monitor epilepsy patients automatic real-time detection and for classification of epileptic seizures. Integrating these logs with Electronic Health Records in Digital Seizure Diaries allows to design more efficient clinical trials and enables improved personalized diagnosis. treatment and disease management.

### **Selected Publications**

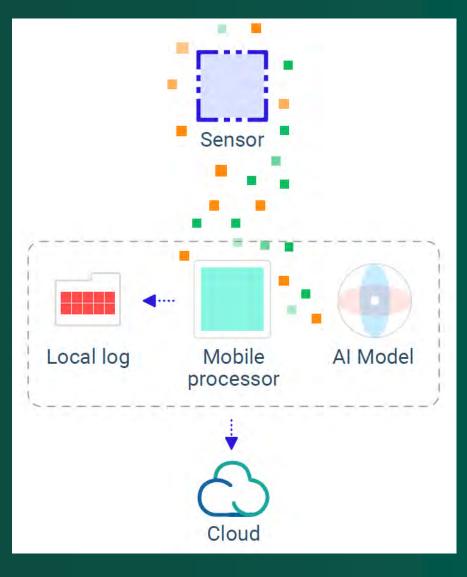
- Trends in Pharmacological Sciences (Cell • *Press*) 2019; 40(8), pp. 577-591.
- EBioMedicine (The Lancet) 2018; 27, pp. • 103-111.
- MICCAI (MLCN) 2020; "SeizureNet: Multispectral deep feature learning for seizure type classification".

### **Partners**

Harvard Medical School. Boston • Children's Hospital, Royal Melbourne Hospital, The Alfred, St. Vincent's Hospital Melbourne, Temple University

Personalized epileptic seizure prediction using electroencephalography (EEG) data measured by implanted electrode sensors

### From Wearables to THINKables



### Table 1 Possible Candidates for Incorporation into Cognitive Sensors Components <sup>a</sup> Type of sensor Application **Bionic Eye** Retinal stimulation electrodes EEG and ECoG electrodes Brain activity monitoring, deep brain-stimulation, controlling prostheses with thought Neural implants Tactile prostheses Artificial skin sensors Nerve- and brain- stimulation Electroceuticals Smart contact lenses Biomarker detection Electrochemical tattoo batteries Tattoo sensors Always-on EEG electrode tattoos Multimodal data measurement Low-cost integrated circuit patches Nano- and Microfluidic sensors, portable DNA sequencers DNA sequencing Molecular sensors Smart pills, nanobiosensors, Biomarker detection functionalized nanoparticles a Abbreviations: ECoG, electrocorticography; EEG, electroencephalography.

# Predicting epileptic seizures

### Motivation

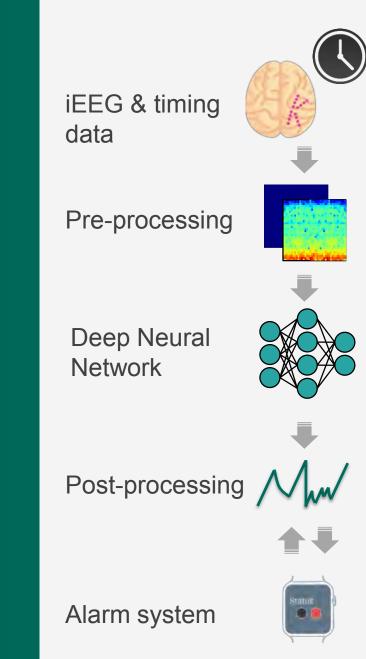
Build algorithms that allow a patient to manage their condition, alerting them to impending seizures

### Data

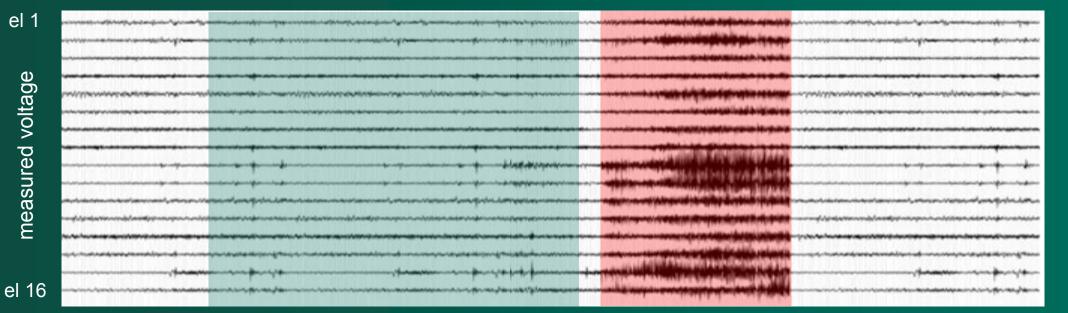
Long-term **intracranial** Electroencephalography (EEG) recordings from 15 patients provided by **Melbourne St. Vincent's Hospital** and **The University of Melbourne**, labelled by expert neurologists

### Approach

- Train **deep neural network** to recognise patient-specific patterns emerging *before* a seizure
- Design a system that allows for **real-time** alarms
- Allow for tuning based on **patient's needs**



### Data selection



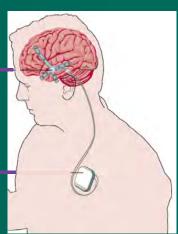
### automatically labelled

preictal (16-1 minutes pre seizure)

expert labelled, time-stamped

ictal (seizure)

time



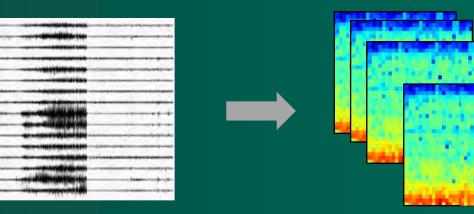
### **Seizure Prediction Task**

Train algorithm to distinguish between preictal and interictal (normal) brain signal Interictal: at least 5 hours away from seizure

IBM Research

### Data pre-processing

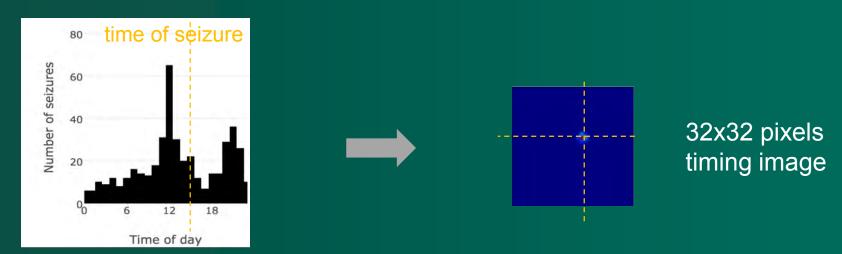
16 channel iEEG signal



16 32x32 pixels spectrograms every 30 seconds

### **Spectral Information**

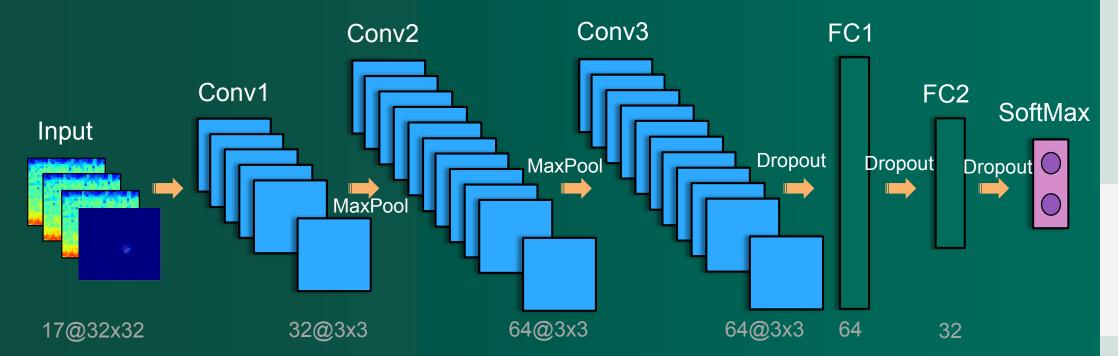
Epileptic seizures correlate with neuronal synchronisation, which can be visualised using spectrograms.



Timing information: Seizures have been shown to follow different circadian rhythms in different patients.

IBM Research

### Neural network architecture



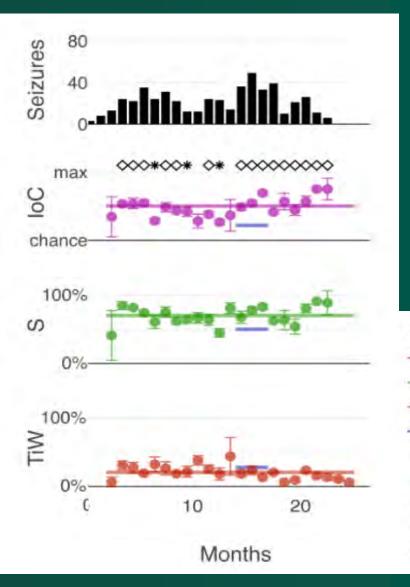
### **Real-Time Classifications**

Network classifies each sample of 30 seconds

•Without post-processing, this would result in one prediction every 30 seconds

• Exploiting the sequential structure of the data, temporal averaging should improve classification accuracy

## Epileptic seizure prediction – study results



# example results for patient 13

- Seizures per month
- Average improvement over chance
- Average sensitivity
- Average time in warning
- Cook et al., 2013
- Month-wise IoC
- Month-wise sensitivity
- Time in warning per month
- \* p<0.05
- ◊ p<0.01</p>

### Study strategy:

- oPseudo-prospective
- ○Spectrograms + time information
- Post-processing (integrate and fire)
- Network retrained once a month
- •**Tunable** by patients (max sensitive vs. least intrusive)

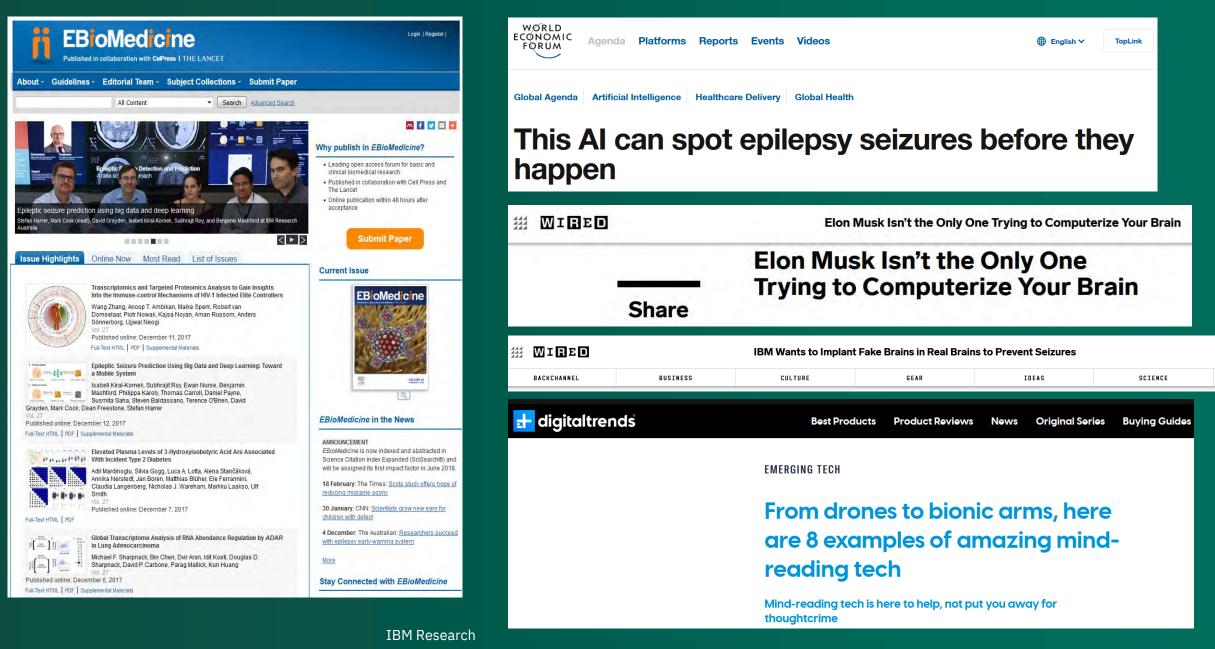
# **Results across all patients for entire duration of study:**

- •Mean sensitivity of 69%
- •Mean time in warning of 27%
- •Mean improvement over chance 42%

# Ultra-low power consumption mobile processor implementation for mobile deployment

### **IBM** Research

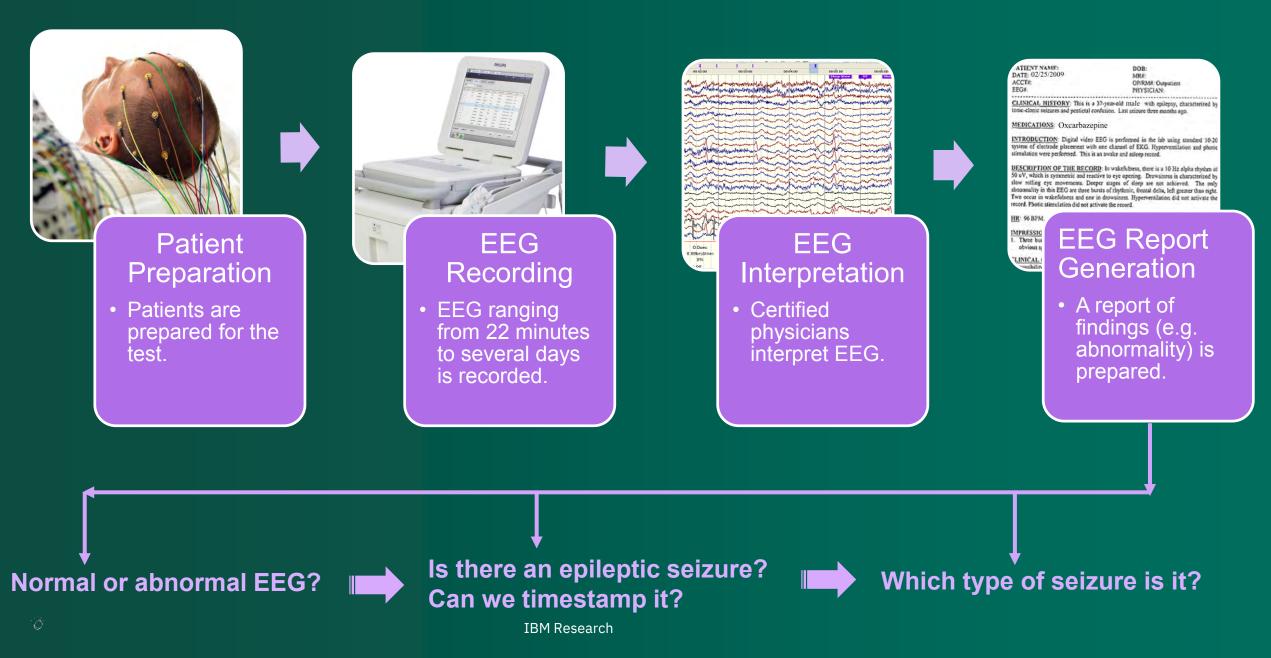
## Precursor: Predicting Epileptic Seizures - Published in EBioMedicine (2018)



## Epileptic seizure detection: re-inventing the epilepsy monitoring unit

IBM Research

## Manual interpretation of scalp EEG – process pipeline



### Automatic interpretation of scalp EEG – data



Seizure type	А	vailable train and te	est data
Label, Type, [Superclass]	Patients	Files	Seconds

#### **Open Source EEG Resources**

Home Overview Downloads

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### Electroencephalography (EEG) Resources

#### Mission

Our goal is to enable deep learning research in neuroscience by releasing the largest publicly available unencumbered database of EEG recordings. This ongoing project currently includes over 30,000 EEGs spanning the years from 2002 to present. Data collected can be used for both research and commercialization purposes.

#### Get Access

To request access to these resources, please fill out <u>this form</u>. You will receive an automaticallygenerated username and password via email. Please be patient since it takes a few minutes to receive the email.

Since these databases are quite large, it is best to transfer them via hard disk. If you are interested in this option, please follow the instructions <u>here</u>.



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#### What's New

- (20200408) Our paper describing our <u>annotation</u> <u>standards</u> for the Temple University Hospital EEG Seizure Corpus has been published and is now available.
- (20200402) As part of IEEE SPMB 2020, we are collaborating with Novela Neurotech and NeuroTechX on the <u>Neureka™ 2020 Epilepsy</u> <u>Challenge</u>.
- (20200328) We have released our simplified <u>EEG scoring software (v3.3.1)</u> to be featured in an upcoming open source seizure detection competition. This version reads a list of seizure events and compares them to the reference annotations of our recent database release: <u>TUH EEG Seizure Corpus (v1.5.1)</u>.



# Identifying epileptic seizure types

### **Motivation:**

- Patients may have more than one type of seizure
- The type of seizure may inform therapy/medication
- Tracking types and each type's rate may further inform medication adjustments
- Type information may help in diagnosis and to make clinical trials more nuanced

### Implementation:

- Convolutional neural networks for binary classifiers
- Focus on preserving spatial electrode information

### Seizure classes investigated:

 Focal/General, Motor/Non-motor, Tonic/Tonic-clonic, Complex-partial/Simple-partial

### ILAE 2017 Classification of Seizure Types Expanded Version<sup>1</sup>

Focal	Onset	Generalized Onset	Unknown Onset
Aware Impaired Awareness Motor Onset automatisms atonic <sup>2</sup> clonic epileptic spasms <sup>2</sup>	Motor tonic-clonic clonic tonic myoclonic myoclonic-tonic-clonic myoclonic-atonic atonic	Motor tonic-clonic epileptic spasms Non-Motor behavior arrest	
hyperk myoclo tonic Non-N autono	tinetic onic <b>lotor Onset</b> omic or arrest ive onal	epileptic spasms Non-Motor (absence) typical atypical myoclonic eyelid myoclonia	
focal to bila	ateral tonic-clonic	<sup>2</sup> Degree of awareness usually is not <sup>3</sup> Due to inadequate information or in	

### What type of epileptic seizure is it?

MACHINE LEARNING IN CLINICAL NEUROIMAGING, IN CONJUNCTION WITH MICCAI, 4 OCTOBER 2020, LIMA - PERU



The Machine GamesBeat Jobs

The Machine Making sense of Al SeizureNet: Multi-Spectral Deep Feature Learning for Seizure Type Classification

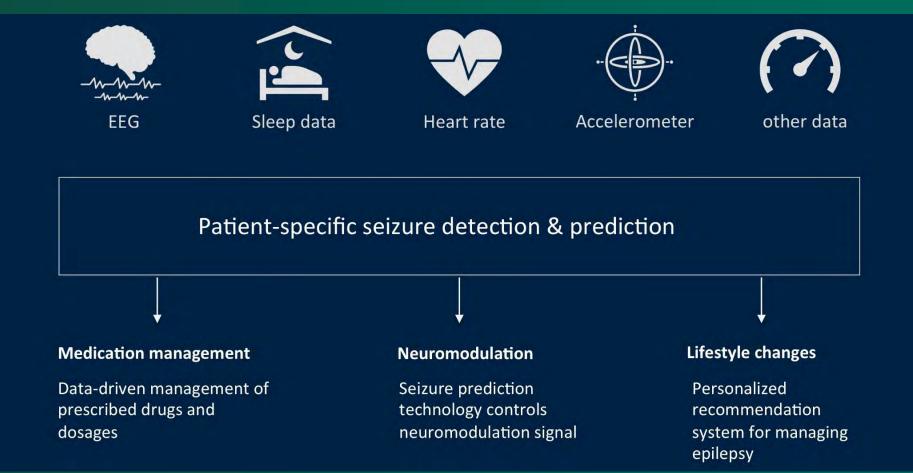
Umar Asif (IBM Research)\*; Subhrajit Roy (IBM Research); Jianbin Tang (IBM Research); Stefan Harrer (IBM Research)

IBM's AI classifies seizures with 98.4% accuracy using EEG data

Special Issue

## Towards a fully automated digital seizure diary

### Current work: multimodal data classification



### Data modalities include:

intracranial EEG, scalp EEG, ECG, body temperature, blood pressure, movement patterns, sleep data, heart rate, video, audio, electronic health records, electrodermal activity, photoplethysmogram



# Find out more...

### Trends in Pharmacological Sciences

Volume 40 Number 8 August 2019 ISSN 0165-6147



Special Issue: Rise of Machines in Medicine

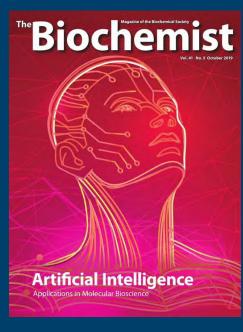


Trends in Pharmacological Sciences

Special Issue: Rise of Machines in Medicine
Review

Artificial Intelligence for Clinical Trial Design

Stefan Harrer,<sup>1,\*</sup> Pratik Shah,<sup>2</sup> Bhavna Antony,<sup>1</sup> and Jianying Hu<sup>3</sup>



### Artificial Intelligence

A new promising way for tackling the 'Pharma Dilemma': artificial intelligence for clinical trials

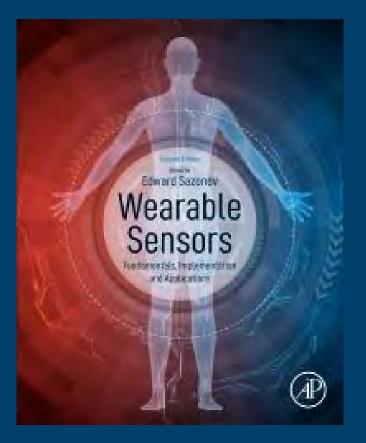
Stefan Harrer, Bhavna Antony, Akram Bayat and Jianying Hu (IBM Research, Australia, MIT Media Lab, USA and IBMT. J. Watson Research Center, USA) Artificial intelligence (AI) is certainly not a panacea for solving the 'Pharma Dilemma', in which the cost of producing new drugs continues to spiral. However, AI can be used to fundamentally change the way we perform essential steps in clinical trial design and execution, from cohort selection to patient monitoring. Merging AI and clinical expertise across engineering and medical disciplines to explore the impact of these changes on trial performance and success rates is one of the most promising leads we have for restoring efficiency and sustainability to the drug development cycle.

CelPress



## ...and read this book:

M. Mirmomeni, T. Fazio, S. v. Cavallar, and S. Harrer "From Wearables to THINKables: Alenabled sensors for health monitoring", in Wearable Sensors – Fundamentals, Implementation and Applications – 2<sup>nd</sup> Edition, ISBN 9780128192467, Academic Press, November 2020.





# The world is our lab





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