



VANDERBILT UNIVERSITY  School of Medicine

Society for Anesthesia & Sleep Medicine


**Top 5 Technologies in
Sleep and Anesthesia**


Jon Wanderer, M.D., M. Phil
Vanderbilt University
Department of Anesthesiology

VANDERBILT UNIVERSITY  School of Medicine

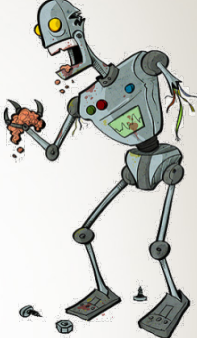
**Artificial Intelligence and
Sleep Medicine:
Hope or Hype?**

Jon Wanderer, M.D., M. Phil
Vanderbilt University
Department of Anesthesiology


VANDERBILT UNIVERSITY  School of Medicine



Are Robot Zombies Going to Take Over Medicine?



Jon Wanderer, M.D., M. Phil
Vanderbilt University
Department of Anesthesiology

VANDERBILT UNIVERSITY  School of Medicine

Goals and Objectives

- Understand the context for the development of artificial intelligence in health care
- Explain how neural networks work
- Describe applications of AI in health care
 - Top 5 Technologies in Sleep and Anesthesia
- Describe limitations of the artificial intelligence

We live in the future



Microsoft | Skype Downloads Skype to Phone Skype Number Features Products - Get help -


Skype Translator

Whether you need to translate English to Spanish, English to French, or communicate in voice or text in dozens of languages, Skype can help you do it all in real time – and break down language barriers with your friends, family, clients and colleagues.

Our **voice translator** can currently translate conversations in 10 languages, including English, Spanish, French, German, Chinese (Mandarin), Italian, Portuguese (Brazilian), Arabic, and Russian.

And our **text translator** is available in **more than 60 languages** for clear, seamless instant messaging. Of course, new languages are being added all the time, so if you don't see the language or dialect you need in our list of supported languages, keep checking back.

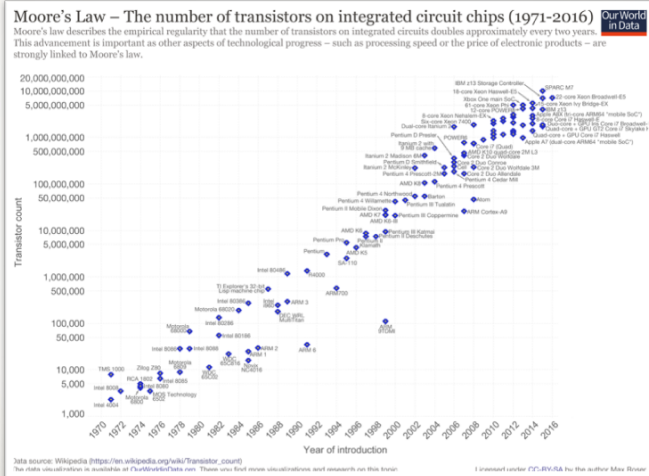
[Get Skype](#)

A screenshot of the Skype Translator interface showing a woman wearing a headset in a video call window. Below her, there are text boxes for input and output, with a small icon of a person speaking.

AI Everywhere



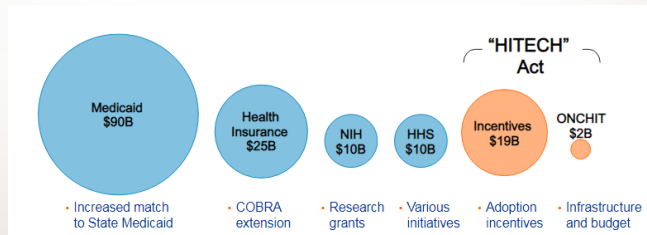
Moore's Law



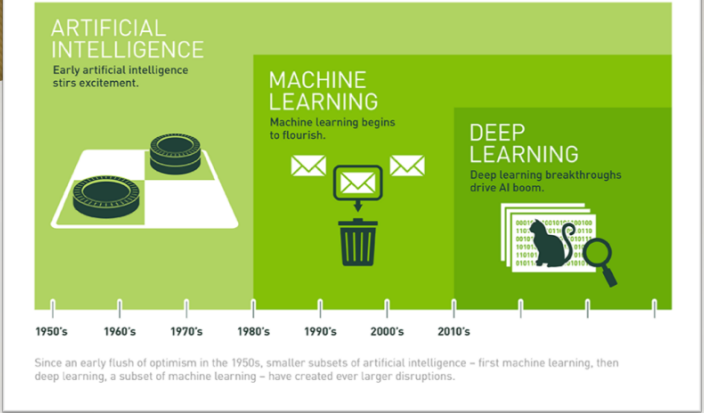
“The number of transistors that can be packed into a given unit of space will roughly double every two years.”

Health Information Technology for Economic and Clinical Health Act (HITECH Act)

- Part of the American Recovery and Reinvestment Act of 2009 (ARRA)
- Created to motivate the implementation of electronic health records (EHR)



VANDERBILT U



ARTIFICIAL INTELLIGENCE
Early artificial intelligence stirs excitement.

MACHINE LEARNING
Machine learning begins to flourish.

DEEP LEARNING
Deep learning breakthroughs drive AI boom.

1950's 1960's 1970's 1980's 1990's 2000's 2010's


Since an early flush of optimism in the 1950s, smaller subsets of artificial intelligence – first machine learning, then deep learning, a subset of machine learning – have created ever larger disruptions.

AI: The theory and development of computer systems able to perform tasks that normally require human intelligence, such as visual perception, speech recognition, decision-making, and translation between languages

Machine Learning: Algorithms and statistical models that computer systems use to progressively improve their performance on a specific task.

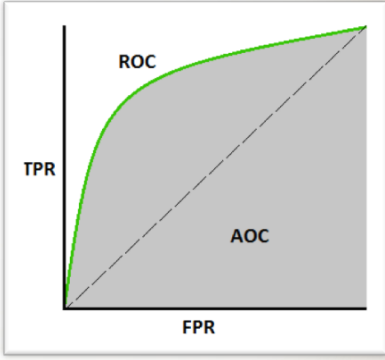
Deep Learning: Learning data representations, as opposed to task-specific algorithms.

<https://www.datasciencecentral.com/profiles/blogs/artificial-intelligence-vs-machine-learning-vs-deep-learning>, accessed 12/10/2018

VANDERBILT UNIVERSITY  School of Medicine

Measuring Classification: AUC ROC

- True Positive Rate = Sensitivity
- False Positive Rate = 1 - Specificity
- AUC = Area under the curve
- ROC = Receiver operating characteristics



AUC=0.5 is chance separation
AUC=1 is perfect separation
AUC=0 has no separation

Roadmap

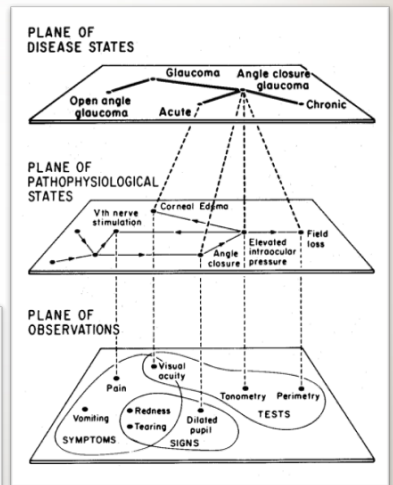
- Understand the context for the development of artificial intelligence in health care
- Explain how neural networks work
- Describe applications of AI in health care
 - Top 5 Technologies in Sleep and Anesthesia
- Describe limitations of the artificial intelligence

Early AI in Medicine

- Initial approach
 - Manipulation of symbolic expressions with rules of inference
 - Expert systems to automate reasoning process of experts

```

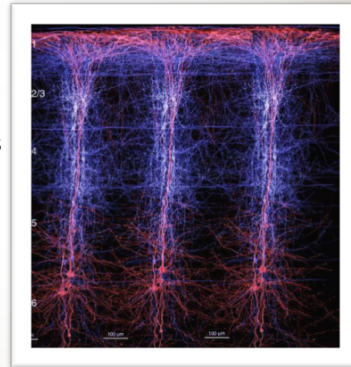
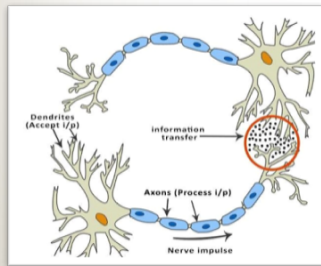
RULE 85
IF {
  1) The site of the culture is blood, and
  2) The Gram stain of the organism is negative, and
  3) The morphology of the organism is rod, and
  4) The patient is a compromised host
THEN { There is suggestive evidence (0.6) that the identity
        of the organism is pseudomonas aeruginosa.
    
```



Shortliffe EH, Davis R, Axline SG, Buchanan BG, Green CC, Cohen SN. Comput Biomed Res. 1975 Aug;8(4):303-20.

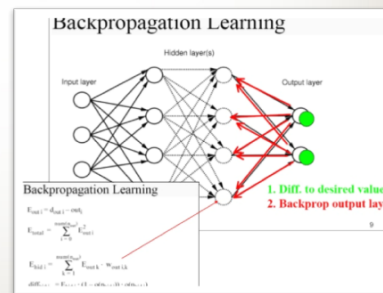
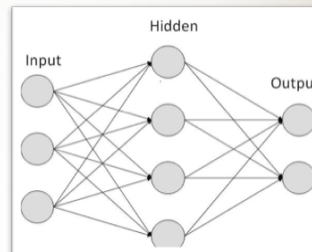
How Actual Intelligence Works

- Layers of neuros
 - Information from outside world
 - Information transfer between neurons
 - Synaptic input can be strong or weak, connections can develop or be pruned
 - Transfer of information between layers of neurons



Neural Networks

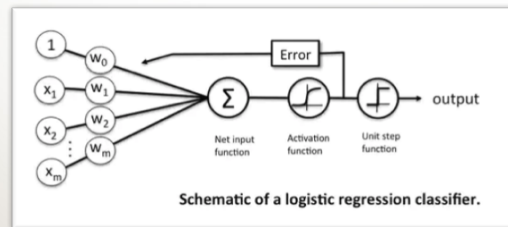
- Artificial neural networks
 - Mimic neurons
 - Neural networks (1960s)
 - Back-propagation (1986)
 - Then computers got fast
- Hidden layers
 - Can represent dataset features
 - Number of hidden factors is specified
 - Inputs to those are not limited
- Convolutional neural network
 - Copies of features are made and averaged
 - Generalizes feature detection from one image area to another



Logistic Regression and NN

$$\text{logit}(p_i) = \ln \left(\frac{p_i}{1 - p_i} \right) = \beta_0 + \beta_1 x_{1,i} + \dots + \beta_M x_m$$

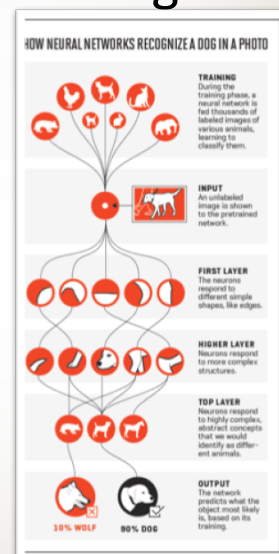
Logistic regression is essentially a single-layer feed forward neural network



How to recognize a dog

- Training
 - Images with labels are fed to an untrained neural network
 - Wolves
 - Dogs
 - Weights are tweaked with back-propagation
- Validation
 - Images without labels are fed to network
 - Initial layer finds small features
 - Higher layer finds structural features
 - Highest lay represents concepts
 - Model performance is analyzed

<http://fortune.com/ai-artificial-intelligence-deep-machine-learning/>, accessed 12/10/2018

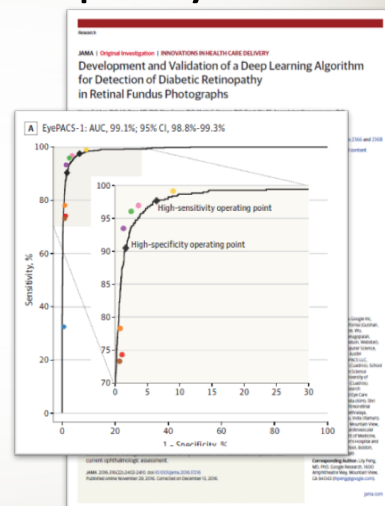


Roadmap


- Understand the context for the development of artificial intelligence in health care
- Explain how neural networks work
- Describe applications of AI in health care
 - Top 5 Technologies in Sleep and Anesthesia
- Describe limitations of the artificial intelligence

Diabetic retinopathy

- Deep convolutional neural network
 - Trained on 128,175 retinal images
 - Separate validation datasets
- Images graded by 54 ophthalmologists
 - Diabetic retinopathy
 - Macular edema
 - Image quality
- Results
 - AUC 0.991, Sensitivity 93%, Specificity 97.5%

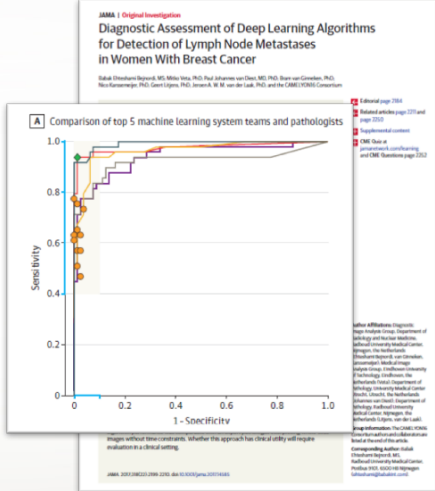


JAMA. 2016;316(22):2402-2410. doi:10.1001/jama.2016.17216

VANDERBILT UNIVERSITY  School of Medicine

Breast Cancer Metastases

- Image data sets
 - 399 whole-slide images
 - 270 training
 - 129 test
 - Metastases: None, Macro, Micro
- Competition of
 - 32 machine learning algorithms
 - 11 pathologists
- Results
 - Varied from AUC 0.556 to 0.994
 - Top 5 algorithms were as good as pathologist without time constraints



JAMA | Original Investigation
Diagnostic Assessment of Deep Learning Algorithms for Detection of Lymph Node Metastases in Women With Breast Cancer
 Sahak Ghahramani, PhD, MS, MD, PhD; Paul Johannes van Diest, MD, PhD; Ryan van Gool, PhD; Nicolaas de Jong, PhD; Gerrit Litjens, PhD; Jeroen M. M. van der Laak, PhD; and the CAMIS-CAMIS Consortium


A Comparison of top 5 machine learning system teams and pathologists

Sensitivity vs 1 - Specificity

Images without time constraints, whether this approach has clinical utility will require evaluation in a clinical setting.

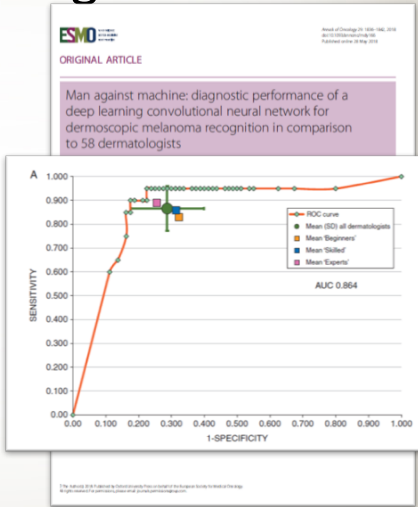
JAMA. 2017;318(22):2199-2210. doi:10.1001/jama.2017.14585

JAMA. 2017;318(22):2199-2210. doi:10.1001/jama.2017.14585

VANDERBILT UNIVERSITY  School of Medicine

Melanoma Diagnosis

- Image data sets
 - 400 whole-slide images
 - 300 training
 - 100 test
 - Melanoma vs benign nevi
- Competition of
 - Google Inception v4 convoluted neural network
 - 58 pathologists
- Results
 - Neural network: AUC 0.86
 - Average pathologist: AUC 0.79



ESMO ORIGINAL ARTICLE

Man against machine: diagnostic performance of a deep learning convolutional neural network for dermoscopic melanoma recognition in comparison to 58 dermatologists


A

Sensitivity vs 1-Specificity

AUC 0.864

Legend: ROC curve, Mean (SD) of dermatologists, Mean 'Beginners', Mean 'Skilled', Mean 'Expert'

Ann Oncol. 2018 Aug 1;29(8):1836-1842. doi: 10.1093/annonc/mdy166.

VANDERBILT UNIVERSITY  School of Medicine

Echo Interpretation

- Image data sets
 - 14,035 echo exams
- CNNs developed to
 - Identify viewpoints
 - Cardiac chamber segmentation in 5 views
 - Calculate volume, LV mass, EF
- Results for diagnostic accuracy
 - HOCM: AUC 0.93
 - Cardiac amyloidosis: 0.87
 - Pulmonary arterial HTN: 0.85

Circulation

ORIGINAL RESEARCH ARTICLE

Fully Automated Echocardiogram Interpretation in Clinical Practice

Feasibility and Diagnostic Accuracy

Editorials, see p 1636 and p 1639

BACKGROUND: Automated cardiac image interpretation has the potential to transform clinical practice in multiple ways, including enabling serial assessment of cardiac function by nonexperts in primary care and rural settings. We hypothesized that advances in computer vision could enable building a fully automated, scalable analysis pipeline for echocardiogram interpretation, including (1) view identification, (2) image segmentation, (3) quantification of structure and function, and (4) disease detection.

METHODS: Using 14 035 echocardiograms spanning a 10-year period, we trained and evaluated convolutional neural network models for multiple tasks, including automated identification of 23 viewpoints and segmentation of cardiac chambers across 5 common views. The segmentation output was used to quantify chamber volumes and left ventricular mass, determine ejection fraction, and facilitate automated determination of longitudinal strain through speckle tracking. Results were evaluated through comparison to manual segmentation and measurements from 1646 echocardiograms obtained during the routine clinical workflow. Finally, we developed models to detect 3 diseases: hypertrophic cardiomyopathy, cardiac amyloid, and pulmonary arterial hypertension.


RESULTS: Convolutional neural networks accurately identified view (eg, 94% for parasternal long axis), including flagging partially obscured cardiac chambers, and enabled the segmentation of individual cardiac chambers. The resulting cardiac structure measurements agreed with study report values (eg, median absolute deviations of 15% to 17% of observed values for left ventricular mass, left ventricular diastolic volume, and left atrial volume). In terms of function, we computed conventional ejection fraction and longitudinal strain measurements (within 2 controls), which agreed with commercial software-derived values (for ejection fraction, median absolute deviation of 1% of observed, but 857 outliers; for strain, median absolute deviation of 3%, n=118, and 9 076, n=118) and demonstrated applicability to serial monitoring of patients with breast cancer for trastuzumab cardiotoxicity. Overall, we found automated measurements to be comparable or superior to manual measurements across 11 internal consistency metrics, the comparison of left atrial and ventricular volumes. Finally, we trained convolutional neural networks to detect hypertrophic cardiomyopathy, cardiac amyloidosis, and pulmonary arterial hypertension with C statistics of 0.93, 0.87, and 0.85, respectively.

CONCLUSIONS: Our pipeline lays the groundwork for using automated interpretation to support serial patient tracking and scalable analysis of millions of echocardiograms acquired within healthcare systems.

© 2018 American Heart Association. All rights reserved. For more information, see the Circulation website at <http://www.ahajournals.org>.

DOI: 10.1161/CIRCULATIONAHA.118.016228

Circulation. 2018;138:1623–1635. DOI: 10.1161/CIRCULATIONAHA

VANDERBILT UNIVERSITY  School of Medicine

Stroke Detection

- Surely we're not using this machine learning stuff yet, right?

FDA permits marketing of clinical decision support software for alerting providers of a potential stroke in patients

For Immediate Release

February 13, 2018

Summary

FDA permits marketing of clinical decision support software for alerting providers of a potential stroke in patients


Release

Today, the U.S. Food and Drug Administration permitted marketing of the Viz AI Contact application, a type of clinical decision support software designed to analyze computed tomography (CT) results that may notify providers of a potential stroke in their patients.

A stroke is a serious medical condition that requires emergency care and can cause lasting brain damage, long-term disability or even death. A stroke occurs if the flow of oxygen-rich blood to a portion of the brain is blocked, also known as an occlusion. According to the Centers for Disease Control and Prevention, stroke is the fifth leading cause of death in the U.S. and is a major cause of serious disability for adults. About 795,000 people in the U.S. have a stroke each year.

"Strokes can cause serious and irreversible damage to patients. The software device could benefit patients by notifying a specialist earlier thereby decreasing the time to treatment. Faster treatment may lessen the extent or progression of a stroke," said Robert Ochoa, Ph.D., acting deputy director for radiological health, Office of In Vivo Diagnostics and Radiological Health in the FDA's Center for Devices and Radiological Health.

The Viz AI Contact application is a computer-aided triage software that uses an artificial intelligence algorithm to

VANDERBILT UNIVERSITY  School of Medicine

Fracture Detection

- But probably just for that stroke stuff, no?

FDA permits marketing of artificial intelligence algorithm for aiding providers in detecting wrist fractures

For Immediate Release
May 24, 2018


Summary
FDA permits marketing of artificial intelligence algorithm for aiding providers in detecting wrist fractures

Release
Today, the U.S. Food and Drug Administration permitted marketing of Imagen OsteoDetect, a type of computer-aided detection and diagnosis software designed to detect wrist fractures in adult patients.

"Artificial intelligence algorithms have tremendous potential to help health care providers diagnose and treat medical conditions," said Robert Ochs, Ph.D., acting deputy director for radiological health, Office of In Vitro Diagnostics and Radiological Health in the FDA's Center for Devices and Radiological Health. "This software can help providers detect wrist fractures more quickly and aid in the diagnosis of fractures."

The OsteoDetect software is a computer-aided detection and diagnostic software that uses an artificial intelligence algorithm to analyze two-dimensional X-ray images for signs of distal radius fracture, a common type of wrist fracture. The software marks the location of the fracture on the image to aid the provider in detection and diagnosis.

OsteoDetect analyzes wrist radiographs using machine learning techniques to identify and highlight regions of distal radius fracture during the review of posterior-anterior (front and back) and medial-lateral (sides) X-ray images of adult wrists. OsteoDetect is intended to be used by clinicians in various settings, including primary care, emergency medicine, urgent care and specialty care, such as orthopedics. It is an adjunct tool and is not intended to replace a

VANDERBILT UNIVERSITY  School of Medicine

Automated Sleep Scoring

- Data sets
 - 10,000 clinical PSGs
 - 5804 research PSGs
- RCNNs developed to identify
 - Sleep stages
 - Sleep disordered breathing
 - Limb movements
- Results for diagnostic accuracy
 - 87.6%, 88.2%, 84.7%
 - All comparable to human experts
 - Almost as good with limited channels (i.e., at-home monitoring)

Journal of the American Medical Association, 2018; 320(18):1840-1850
doi:10.1001/jama.2018.11371
Advance Access Publication Date: 18 November 2018
Research and Applications

Research and Applications

Expert-level sleep scoring with deep neural networks

Siddharth Biswal,¹ Haocq Sun,² Balaji Goparaju,^{2,3} M Brandon Westover,^{2,4} Jitendra Sun,^{1,4} and Matt T Hasek^{2,1,4}

¹School of Computational Science and Engineering, Georgia Institute of Technology, Atlanta, GA, USA, ²Neurology Department, Massachusetts General Hospital, Wing 708, Boston, MA, USA and ³Division of Sleep Medicine, Harvard Medical School, Boston, MA, USA

⁴These authors contributed equally to this work
Corresponding Author: M. Brandon Westover, Massachusetts General Hospital, 55 Fruit Street, Boston, MA 02114, USA; westover@mgah.harvard.edu

Received 10 April 2018; revised 17 August 2018; editorial decision 14 September 2018; accepted 27 September 2018


ABSTRACT

Objective: Scoring laboratory polysomnography (PSG) data remains a manual task of visually annotating 3 primary categories: sleep stages, sleep disordered breathing, and limb movements. Attempts to automate this process have been hampered by the complexity of PSG signals and physiological heterogeneity between patients. Deep neural networks, which have recently achieved expert-level performance for other complex medical tasks, are ideally suited to PSG scoring, given sufficient training data.

Methods: We used a combination of deep recurrent and convolutional neural networks (RCNN) for supervised learning of clinical labels designating sleep stages, sleep apnea events, and limb movements. The data for testing and training were derived from 10 000 clinical PSGs and 5004 research PSGs.

Results: When trained on the clinical dataset, the RCNN reproduces PSG diagnostic scoring for sleep staging, sleep apnea, and limb movements with accuracies of 87.6%, 88.2%, and 84.7% on held-out test data, a level of performance comparable to human experts. The RCNN model performs equally well when tested on the independent research PSG database. Only small reductions in accuracy were noted when training on limited channels to mimic at-home monitoring devices: frontal leads only for sleep staging, and thoracic limb signals only for the apnea-hypopnea index.

Conclusions: By creating accurate deep learning models for sleep scoring, our work opens the path toward broader and more timely access to sleep diagnostics. Accurate scoring automation can improve the utility and efficiency of in-lab and at-home approaches to sleep diagnosis, particularly extending the reach of sleep expertise beyond specialty clinics.

VANDERBILT UNIVERSITY  School of Medicine

Narcolepsy Diagnosis


- Data sets
 - 3,000 PSGs
- Multiple approaches to identify
 - Sleep stages
 - Type-1 Narcolepsy
- Results for accuracy
 - 87%
 - Better than any one scorer
 - For T1N, 96% specific, 91% sensitive

ARTICLE
DOI: 10.1093/ncn/nay022 OPEN

Neural network analysis of sleep stages enables efficient diagnosis of narcolepsy

ens B. Stephansen^{1,2}, Alexander N. Olesen^{1,2,3}, Mads Olesen^{1,2,3}, Aditya Ambati¹, Eileen B. Leary¹, Wyatt E. Moore², Oscar Carrillo¹, Ling Lin¹, Kang Han⁴, Han Yan¹, Yun L. Sun⁴, Ven Davuluri^{5,6}, Sabine Schulz^{2,6}, Lucie Barateau^{2,6}, Birgit Hogg⁷, Amira Stefan⁷, Seung Chul Hong⁷, Tae Won Kim⁸, Fabio Pizzi^{9,10}, Giuseppe Piazzi^{9,10}, Stefano Vandi^{9,10}, Elena Antelmi^{9,10}, Dimitri Perrin¹¹, Samuel T. Kuna¹², Ayla K. Schweitzer¹³, Clote Kushida¹⁴, Paul E. Peppard¹⁴, Helge B.D. Sorensen¹⁵, Poul Jemum¹⁶ & Immanuel Mignot¹




Abstract Analysis of sleep for the diagnosis of sleep disorders such as Type-1 Narcolepsy (T1N) currently requires visual inspection of polysomnography records by trained scoring technicians. Here, we used neural networks to approximately 3,000 normal and abnormal sleep recordings to automate sleep stage scoring, producing a hypersensivity graph—a probability distribution conveying more information than classical hypnograms. Accuracy of sleep stage scoring was validated in 70 subjects assessed by six scorers. The best model performed better than any individual scorer (87% versus consensus). It also reliably scores sleep stages 0.5 s instead of 30 s scoring epochs. A T1N marker based on unusual sleep stage overlaps achieved a specificity of 96% and a sensitivity of 91%, validated in independent datasets. Addition of HLA-DQB1*06:02 typing increased specificity to 99%. Our method can reduce time spent on sleep clinics and automate T1N diagnosis. It also opens the possibility of diagnosing T1N using home sleep studies.

VANDERBILT UNIVERSITY  School of Medicine

Sleep Sound Signatures

- Smartphone sonar
 - Emits frequency-modulated sounds
 - Listens to reflections, tracks chest/abd movement
 - Identifies obstructive, central and hypopnea events
- Accuracy of ApneaApp
 - 37 patients, 296 hours of observation
 - 99.57%, 98.70, 95.33% (correlation coefficient vs PSG)

Contactless Sleep Apnea Detection on Smartphones

Rajalakshmi Nandakumar  Shyamnath Gollakota  Nathaniel Watson M.D. 
Computer Science and Engineering University of Washington rajal@uw.edu Computer Science and Engineering University of Washington gollay@uw.edu UW Medicine Sleep Center University of Washington nwatson@uw.edu

Abstract We present a contactless solution for detecting sleep apnea events on smartphones. To achieve this, we introduce a novel system that monitors the minute chest and abdomen movements caused by breathing on smartphones. Our system works with the phone away from the subject and can simultaneously identify and track the fine-grained breathing movements from multiple subjects. We do this by transforming the phone into an active sonar system that emits frequency-modulated sound signals and listens to their reflections; our design monitors the minute changes in these reflections to extract the chest movements. Results from a home bedroom environment shows that our design operates effectively at distances of up to a meter and works even with the subject under a blanket.

Building on the above system, we develop algorithms that identify various sleep apnea events including obstructive apnea, central apnea, and hypopnea from the sensor reflections. We deploy our system at the UW Medicine Sleep Center at Harborview and perform a clinical study with 37 patients for a total of 296 hours. Our study demonstrates that the number of respiratory events identified by our system is highly correlated with the ground truth and has a correlation coefficient of 0.9957, 0.9860, and 0.9533 for central apnea, obstructive apnea and hypopnea respectively. Furthermore, the average error in computing of rates of apnea and hypopnea events is as low as 1.9 events/hour.

CATEGORIES AND SUBJECT DESCRIPTIONS
1.13 Computer Applications: 1.16 and Medical Sciences

GENERAL TERMS
Design, Human Factors, Algorithms

KEYWORDS
Mobile Health, Sleep Apnea, Phone Sonar, Contactless Breathing Monitoring

1. INTRODUCTION
Sleep apnea is a common medical disorder that occurs when breathing is disrupted during sleep. It is estimated to affect more than 18 million American adults [1, 4] and is linked to attention deficit/hyperactivity disorder, high blood pressure, diabetes, heart disease, stroke, and increased motor vehicle accidents [4, 39]. Diagnosing sleep apnea in the clinic requires the polysomnography test which is an expensive, time-consuming and labor intensive process. It requires a trained technician to attach and monitor various sensors on the patient for the sleep duration and is typically associated with long waiting lists [11]. While portable recording systems are being developed for use in home settings, they require instrumenting either the patient [25, 26, 38] or the bed [16] with various sensors and need still require a trained technician to setup the recording system [16].

In this paper we ask the following question: Can we leverage smartphones to detect sleep apnea events without the need for sensor instrumentation? The key challenge is that detecting sleep apnea events requires tracking the fine-grained abdomen and chest movements due to breathing [16]. While the iPhone Respiratory app [42] can track the breathing movements, it requires placing the phone on the body between the elbow and the stomach and hence is intrusive. Vision based solutions [43] can track these movements without instrumenting users, but are limited to line-of-sight and good lighting conditions and hence are not applicable to the sleep environment, i.e., in the dark or under a blanket.

We introduce a novel contactless system that tracks the chest and abdomen movements via smartphones and works in the sleep environment. It monitors work this abstract from the user and can




Figure 1. Sensors used in the polysomnography test. The figure shows all the sensors used in the test along with the data collection tank. Polysomnography is used to diagnose various sleep disorders including sleep apnea. The goal is to use a smartphone to detect sleep apnea events without any sensors on the human body.


VANDERBILT UNIVERSITY  School of Medicine

Attack of the Sleep Apps!

- Sleep.ai
 - Track your snoring
 - Track your grinding

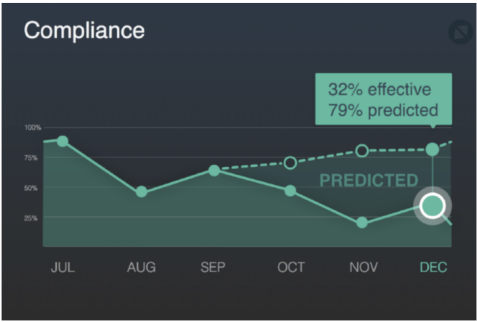
- One scientific app for Grinding, Snoring and Obstructive Sleep Apnea
- Proof that you grind or snore
- Send the sound samples to your dentist or doctor for official sleep bruxism diagnose




VANDERBILT UNIVERSITY  School of Medicine

CPAP Compliance

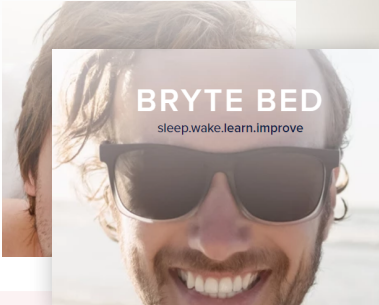
- Somnoware
 - Prediction modeling for short and long-term compliance
 - Data fed from EHR
 - Demographics
 - Comorbidities
 - Prior labs
 - Questionnaire data



VANDERBILT UNIVERSITY  School of Medicine

AI-Powered Mattress?!?


- Switching over to full AI hype mode...



Are you sleeping on a Dead Bed?

The majority of beds used today are built on 19th century technology (static foam, springs, etc). Imagine the impact better sleep technology could have on your health, productivity and happiness.

We took an every day object and created an intelligent sleep platform that will transform your sleep experience and your life. (You'll never want to sleep on a dead bed again.)

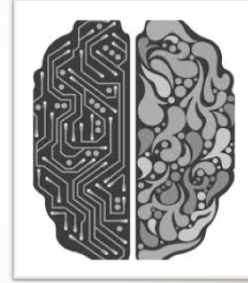
VANDERBILT UNIVERSITY  School of Medicine

AI-Powered Mattress?!?

BED FEATURE	DEAD BED ¹	DEAD BED + BASIC TECH ¹	BRYTE BED
	BRYTE FEATURES		
Support Type	Foam, Springs or Air Bed	Foam, Springs or Air Bed	Hi-Res Dynamic Support
Dynamic Coils™ 100 Dynamic Coils into 16 zones with real-time adjustments			
Real Time Support Adjustments	-	Some	<input checked="" type="checkbox"/>
Dynamic Support +			
As low as \$166/mo. Learn more		QUEEN – \$5,950 ▾	ADD TO CART
Dynamic Dual Sides™ +			
AI-Based Sleep Management	-	-	<input checked="" type="checkbox"/>
Personal Sleep Expert +			
Improves Over Time	-	-	<input checked="" type="checkbox"/>
Personalized Learning +			
Relaxation Support	-	-	<input checked="" type="checkbox"/>
Dynamic Lull™ +			
Nightly Bed & Room Preparation	-	-	<input checked="" type="checkbox"/>

AI in Medicine

- Faster, cheaper computers have enabled cool technology
- Good algorithms exist for image interpretation and complex pattern recognition (i.e., PSG)
- Likely will make sleep studies more efficient
- Unclear if they will make your mattress work better



Roadmap

- Understand the context for the development of artificial intelligence in health care
- Explain how neural networks work
- Describe applications of AI in health care
 - Top 5 Technologies in Sleep and Anesthesia
- Describe limitations of the artificial intelligence

The Barrier of Meaning

- AI still doesn't understand the meaning of things
 - “The bareheaded man needed a hat”
 - “The bear headed man needed a hat”



<https://www.nytimes.com/2018/11/05/opinion/artificial-intelligence-machine-learning.html>, accessed 12/17/2018

Hackable

- Minor changes can disrupt AI-based systems

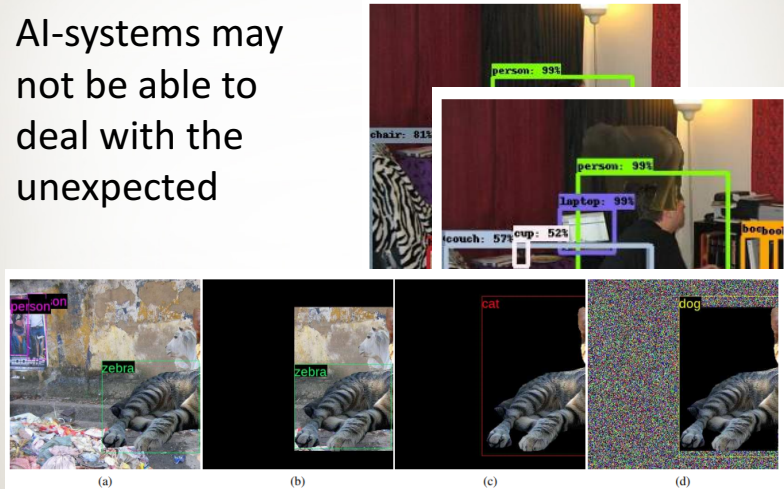


Using this methodology, we evaluate the efficacy of physical adversarial manipulations on real objects. With a perturbation in the form of only black and white stickers, we attack a real stop sign, causing targeted misclassification in 100% of the images obtained in lab settings, and in 84.8% of the captured video frames obtained on a moving vehicle (field test) for the target classifier

Robust Physical-World Attacks on Deep Learning Models. arXiv:1707.08945

Confusable

- AI-systems may not be able to deal with the unexpected



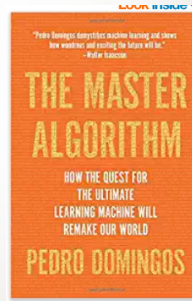
The Black Box

- What hidden factors are being used?
 - Large numbers of complicated, weak connections
 - Not interpretable, in general
 - Initial weights are set randomly, so same NN with same data set will generate different features
 - No correct NN, just modeled relationship between inputs and outputs



AI Taking Over

- “People worry that computers will get too smart and take over the world, but the real problem is that they’re too stupid and they’ve already taken over the world.”
 - Pedro Domingos




AI and Healthcare

- What’s driving adoption of AI?
 - Digital imaging > Human interpretation
 - Digitization of health-related data and sharing
 - Adaptability of deep learning to heterogenous data
 - Capacity of deep learning for hypothesis generation
 - Potential to streamline workflow / empower patients
 - Rapid diffusion of deep learning tools
 - Better, faster technology



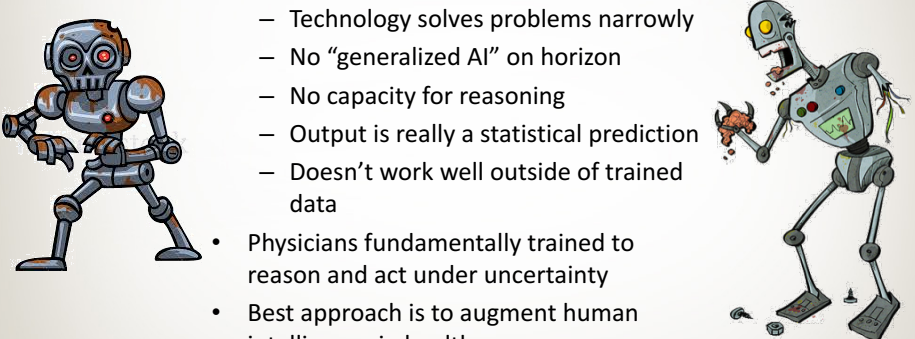
Stead WW. Clinical Implications and Challenges of Artificial Intelligence and Deep Learning. JAMA. 2018 Sep 18;320(11):1107-1108.


VANDERBILT UNIVERSITY  School of Medicine

Are Robot Zombies Going To Take Over Medicine?

- Seems unlikely
 - Technology solves problems narrowly
 - No “generalized AI” on horizon
 - No capacity for reasoning
 - Output is really a statistical prediction
 - Doesn’t work well outside of trained data
- Physicians fundamentally trained to reason and act under uncertainty
- Best approach is to augment human intelligence in health care
 - AI = Augmented Intelligence

Stead WW. Clinical Implications and Challenges of Artificial Intelligence and Deep Learning. JAMA. 2018 Sep 18;320(11):1107-1108.



VANDERBILT UNIVERSITY  School of Medicine

Thanks!

Questions?

