

Artificial Intelligence in Healthcare Analytics

Wei-Hung Weng, MD, MMSc

NUS-MIT Healthcare Analytics Datathon 2017

Jun 30, 2017



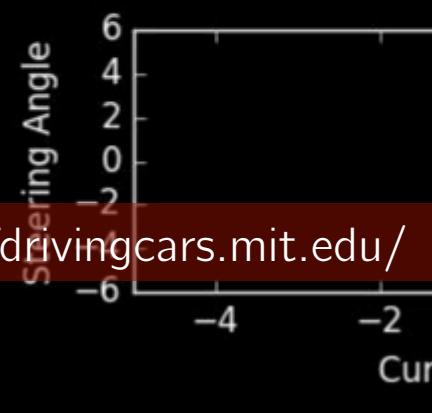
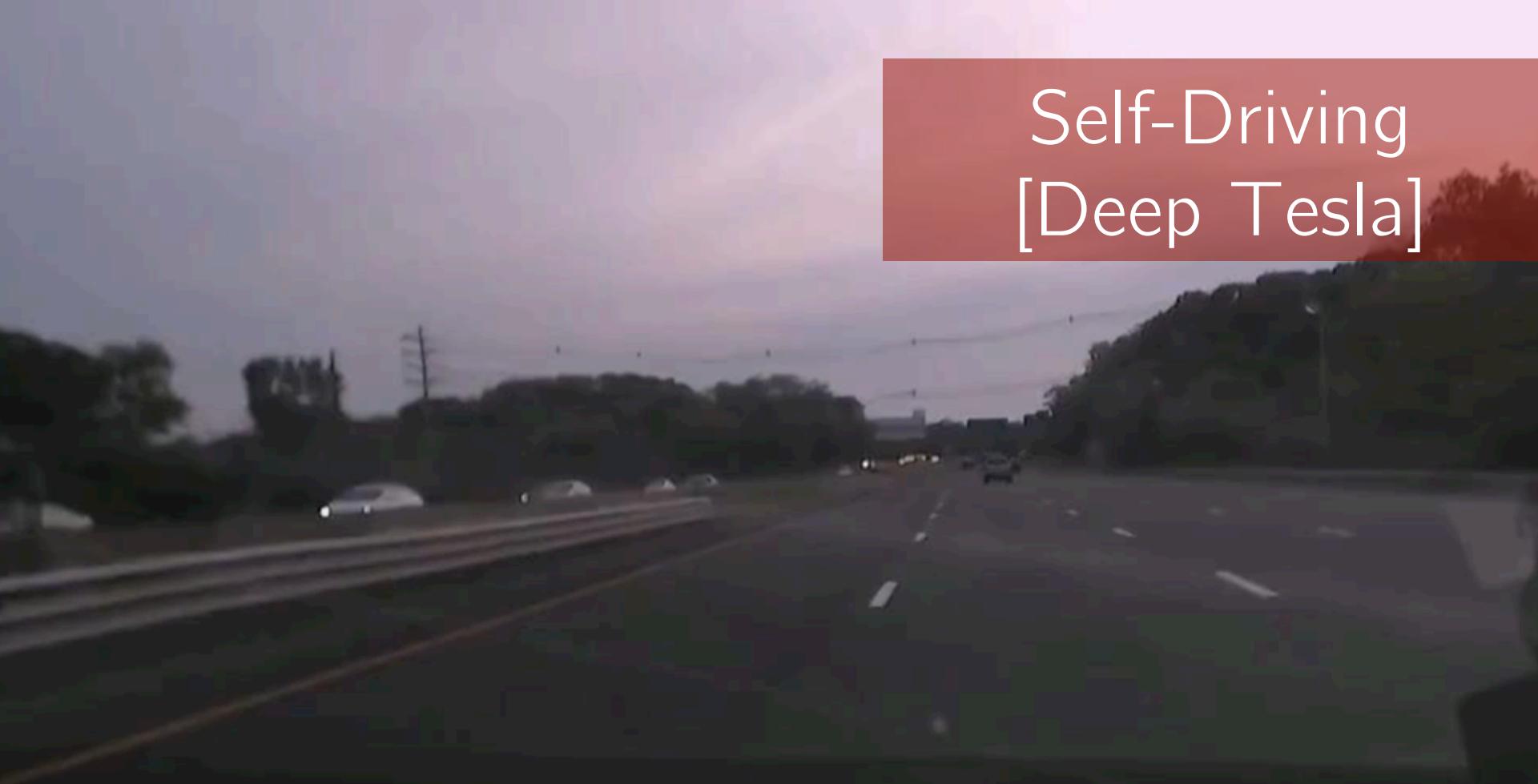
Massachusetts
Institute of
Technology

Disclosure

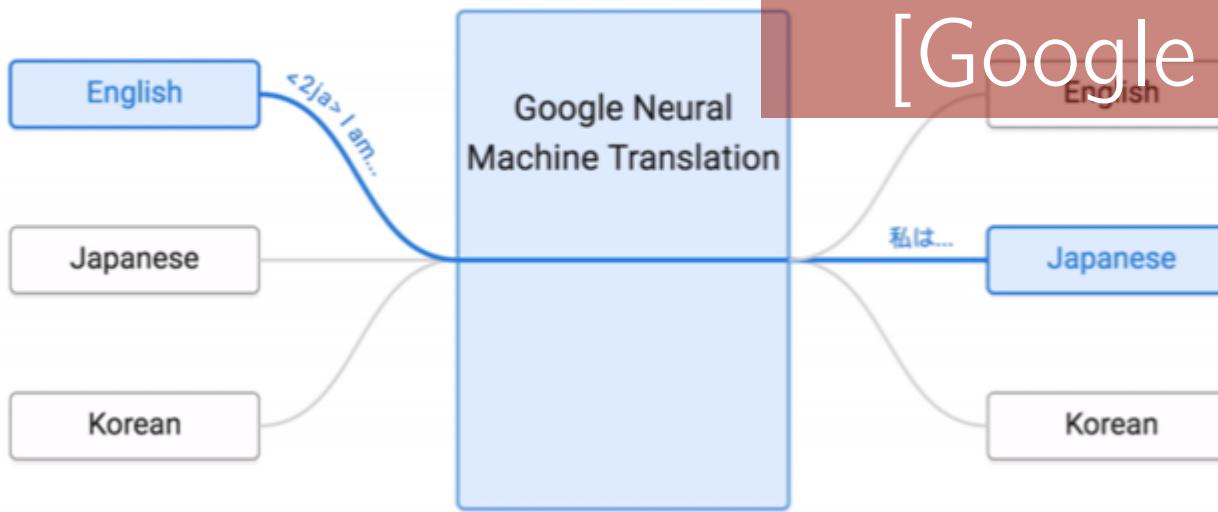
- No conflict of interest

- Artificial intelligence (AI) is defined by the American cognitive scientist Marvin Minsky as *the science of making machines do things that would require intelligence if done by man.*

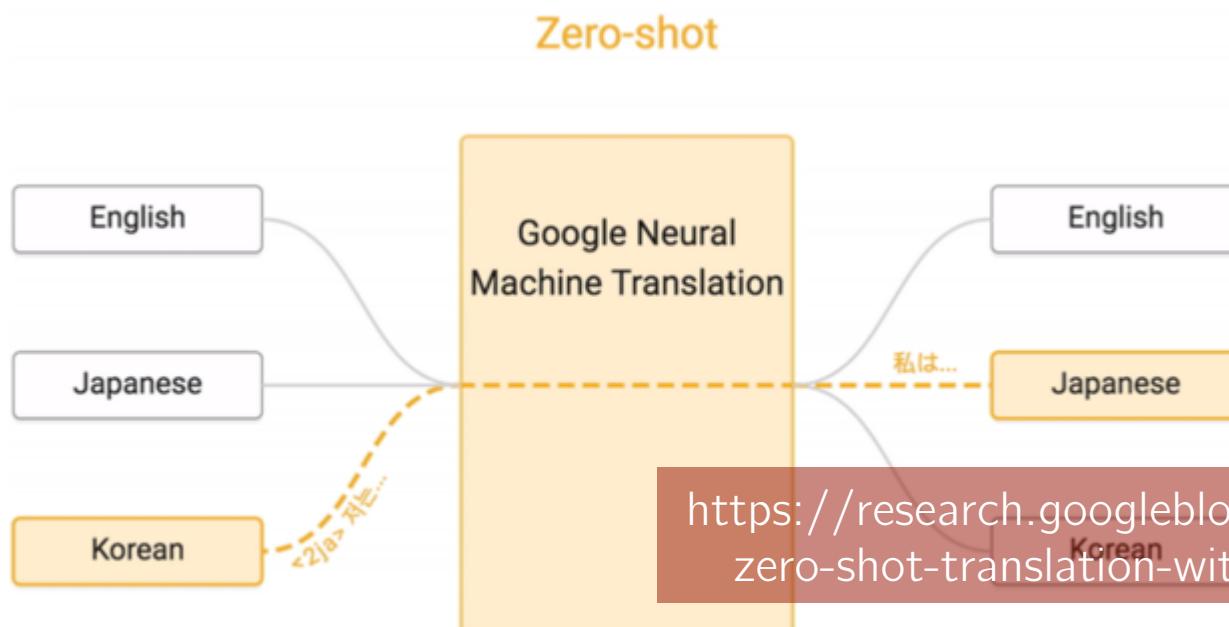
Self-Driving [Deep Tesla]



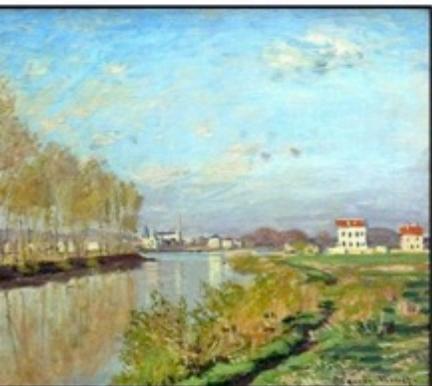
Translation [Google NMT]



Zero-shot



Monet ↪ Photos



Monet → photo



photo → Monet

Zebras ↪ Horses

Style Transfer [CycleGAN]

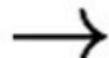


zebra → horse



horse → zebra

<https://github.com/junyanz/CycleGAN>



Photograph



Monet



Van Gogh



Go Playing [DeepMind AlphaGo]



<https://twitter.com/DeepMindAI/status/867996695778410497/photo/1>

Negotiating / Bargaining [Facebook AI Research]

you and

You: I'd like the hat and balls

Fellow Turker: I want the hat too, but I can let you have the books

You: I don't care about the books, you can have them and 1 ball

Fellow Turker: 2

Number You Get

0

0

0

Turker is typing ...

Type Message Here:

Message

Send

<https://code.facebook.com/posts/1686672014972296/deal-or-no-deal-training-ai-bots-to-negotiate?pnref=story>

TRUE?

Technology Will Replace Many Doctors, Lawyers, and Other Professionals

by Richard Susskind and Daniel Susskind

OCTOBER 11, 2016

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<https://hbr.org/2016/10/robots-will-replace-doctors-lawyers-and-other-professionals>

Brief History

- Symbolic AI, rule-based
 - Expert system
 - Mimicking human decision making process
 - Human curated features
 - Watson
-
- MYCIN (Stanford)
 - INTERNIST-1 (U Pittsburg)

-----PATIENT-1-----
1) Patient's name: (first-last)
** **FRED SMITH**
2) Sex:
** **MALE**
3) Age:
** **55**
4) Have you been able to obtain positive cultures from a site
at which Fred Smith has an infection?
** **YES**

-----INFECTION-1-----

- 5) What is the infection?
** **PRIMARY-BACTEREMIA**
6) Please give the date and approximate time when signs or symptoms
of the primary-bacteremia (INFECTION-1) first appeared. (mo/da/yr)
** **MAY 5, 1975**

The most recent positive culture associated with the
primary-bacteremia (INFECTION-1) will be referred to as:

-----CULTURE-1-----

- 7) From what site was the specimen for CULTURE-1 taken?
** **BLODD**
= BLOOD
8) Please give the date and time when this blood culture
(CULTURE-1) was obtained. (mo/da/yr)
** **MAY 9, 1975**

The first significant organism from this blood culture
(CULTURE-1) will be referred to as:

-----ORGANISM-1-----

- 9) Enter the identity of ORGANISM-1:
** **UNKNOWN**

{typically the identity is not known and must be inferred}

- 10) Is ORGANISM-1 a rod or coccus (etc.):
** **ROD**
11) The gram stain of ORGANISM-1:
** **GRAMNEG**
12) Did ORGANISM-1 grow aerobically?
** **YES (.8)**

My therapy recommendation will be based on the following probable infection(s) and potential causative organism(s):

INFECTON-1 is PRIMARY-BACTEREMIA

{possible identities}

- <Item 1> The identity of ORGANISM-1 may be PSEUDOMONAS-AERUGINOSA
- <Item 2> The identity of ORGANISM-1 may be KLEBSIELLA-PNEUMONIAE
- <Item 3> The identity of ORGANISM-1 may be E.COLI
- <Item 4> The identity of ORGANISM-1 may be BACTEROIDES-FRAGILIS
- <Item 5> The identity of ORGANISM-1 may be ENTEROBACTER
- <Item B> The identity of ORGANISM-1 may be PROTEUS-NON-MIRABILIS

MYCIN

46) On a scale of 0 to 4, where higher numbers indicate increasing severity how would you rate Fred Smith's degree of sickness?

** 3

47) Does Fred Smith have a clinically significant allergic reaction to any antimicrobial agent?

** NO

48) Fred Smith's weight in kilograms (or <number> POUNDS):

** 70

{note that 2 drugs cover for 6 potential organisms)

[Rec 1] My preferred therapy recommendation is as follows:

In order to cover for Items <1 2 3 5 6>:

Give: GENTAMICIN

Dose: 119 mg (1.7 mg/kg) q8h IV [or IM] for 10 days

Comments: Modify dose in renal failure

In order to cover for Item <4>:

Give: CLINDAMYCIN

Dose: 595 mg (8.5 mg/kg) q6h IV [or IM] for 14 days

Comments: If diarrhea or other GI symptoms develop, patient should be evaluated for possible pseudomembranous colitis.

Do you wish to see the next choice therapy?

** Y {alternative choices are available}

Which, If any, of the above drugs do you wish eliminated from consideration?

** CLINDAMYCIN

[Rec 2] Next best therapy recommendation:

In order to cover for Items <2 3 4 5 6>:

Give: CHLORAMPHENICOL

Szolovits, Artificial
Intelligence in Medicine 1982

(a) ** HOW DID YOU DECIDE THAT ORGANISM-1 MIGHT BE AN E.COLI?

I used RULE021 to conclude that the identity of ORGANISM-1 is e.coli. This gave a cumulative CF of (.47).

Then I used RULE084 to conclude that the identity of ORGANISM-1 is e.coli. This gave a cumulative CF of (.55).

Finally, I used RULE003 to conclude that the identity of ORGANISM-1 is e.coli. This gave a cumulative CF of (.74).

(b) ** DID YOU USE RULE 163 TO FIND OUT ANYTHING ABOUT ORGANISM-1?

RULE163 was tried in the context of ORGANISM-1, but it failed because it is not true that the patient has had a genito-urinary tract manipulative procedure (clause 3).

(c) ** DID RULE 116 TELL YOU ANYTHING ABOUT INFECTION-1?

No. RULE116 would be relevant to the primary-bacteremia when applied to ORGANISM-1.

But clause 2 ("the gram stain of the organism is not known") was already known to be false for ORGANISM-1, so the rule was never tried.

(d) ** WHY DIDN'T YOU CONSIDER STREPTOCOCCUS AS A POSSIBILITY FOR ORGANISM-1?

The following rule could have been used to determine that the identity of ORGANISM-1 was streptococcus: RULE033

But clause 2 ("the morphology of the organism is coccus") was already known to be false for ORGANISM-1, so the rule

INTERNIST-I

ABDOMEN GUARDING INVOLUNTARY LOCALIZED ?

NO

Please Enter Findings of TRANSFUSION <S> HX

***GO**

TRANSFUSION <S> MULTIPLE HX 7

NO

DISREGARDING: SKIN SPIDER ANGIOMATA, CREATININE BLOOD INCREASED,
UREA NITROGEN BLOOD 60 TO 100

CONSIDERING: FECES LIGHT COLORED, JAUNDICE, LIVER ENLARGED
SLIGHT, ALKALINE PHOSPHATASE BLOOD GTR THAN 2 TIMES NORMAL, SGOT
GTR THAN 400, WBC GTR THAN 30000, SGPT 200 TO 600

PURSUING: HEPATIC LEPTOSPIROSIS

CONCLUDE: HEPATIC LEPTOSPIROSIS

DISREGARDING: SKIN SPIDER ANGIOMATA, UREA NITROGEN BLOOD 60 TO 100

CONSIDERING: OLIGURIA HX, CREATININE BLOOD INCREASED

RULEOUT: RENAL LEPTOSPIROSIS, GLOMERULONEPHRITIS ADVANCED CHRONIC,
LEAD NEPHROPATHY, GLOMERULONEPHRITIS ACUTE, PYELONEPHRITIS
CHRONIC, DIABETIC NEPHROPATHY

Problems

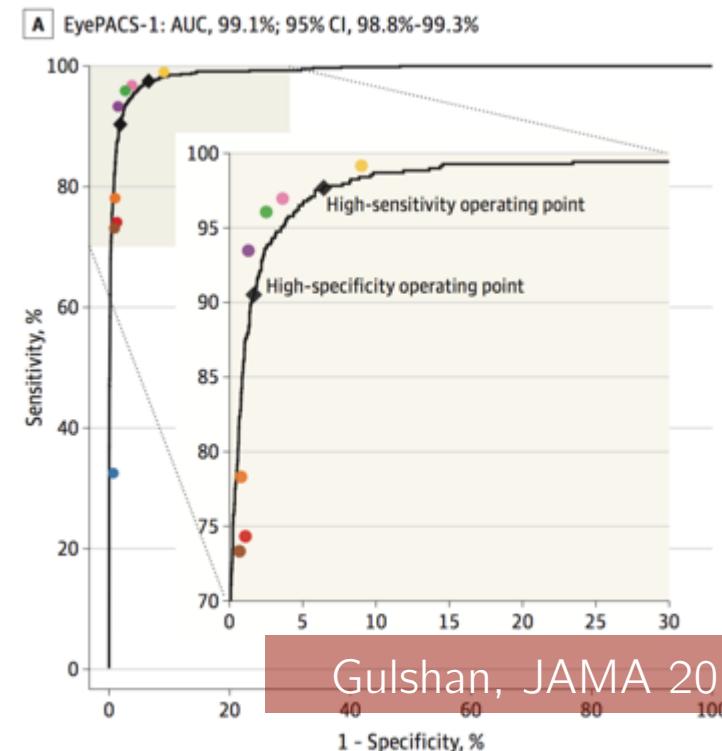
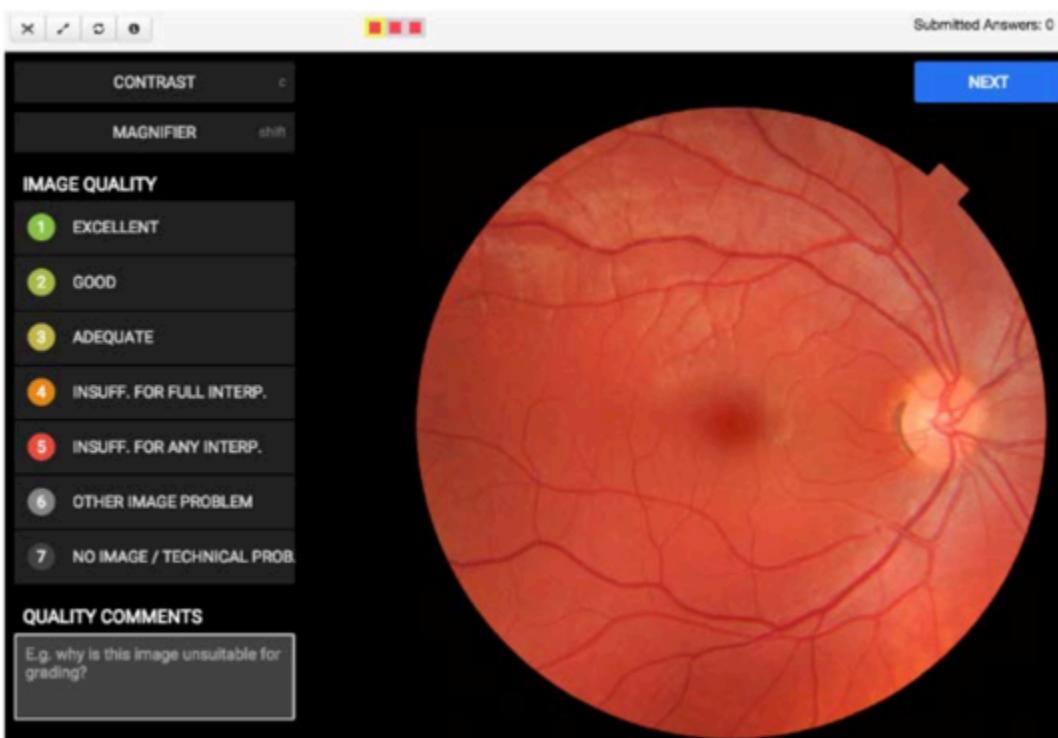
- Could not fit into clinical workflow
- Incomplete
- Expert-needed
- Can't deal with uncertainty
- Poor generalization

Now?

- Symbolic → Data-driven
- Rule-based → Learning-based
- May be able to deal with uncertainty

Development and Validation of a Deep Learning Algorithm for Detection of Diabetic Retinopathy in Retinal Fundus Photographs

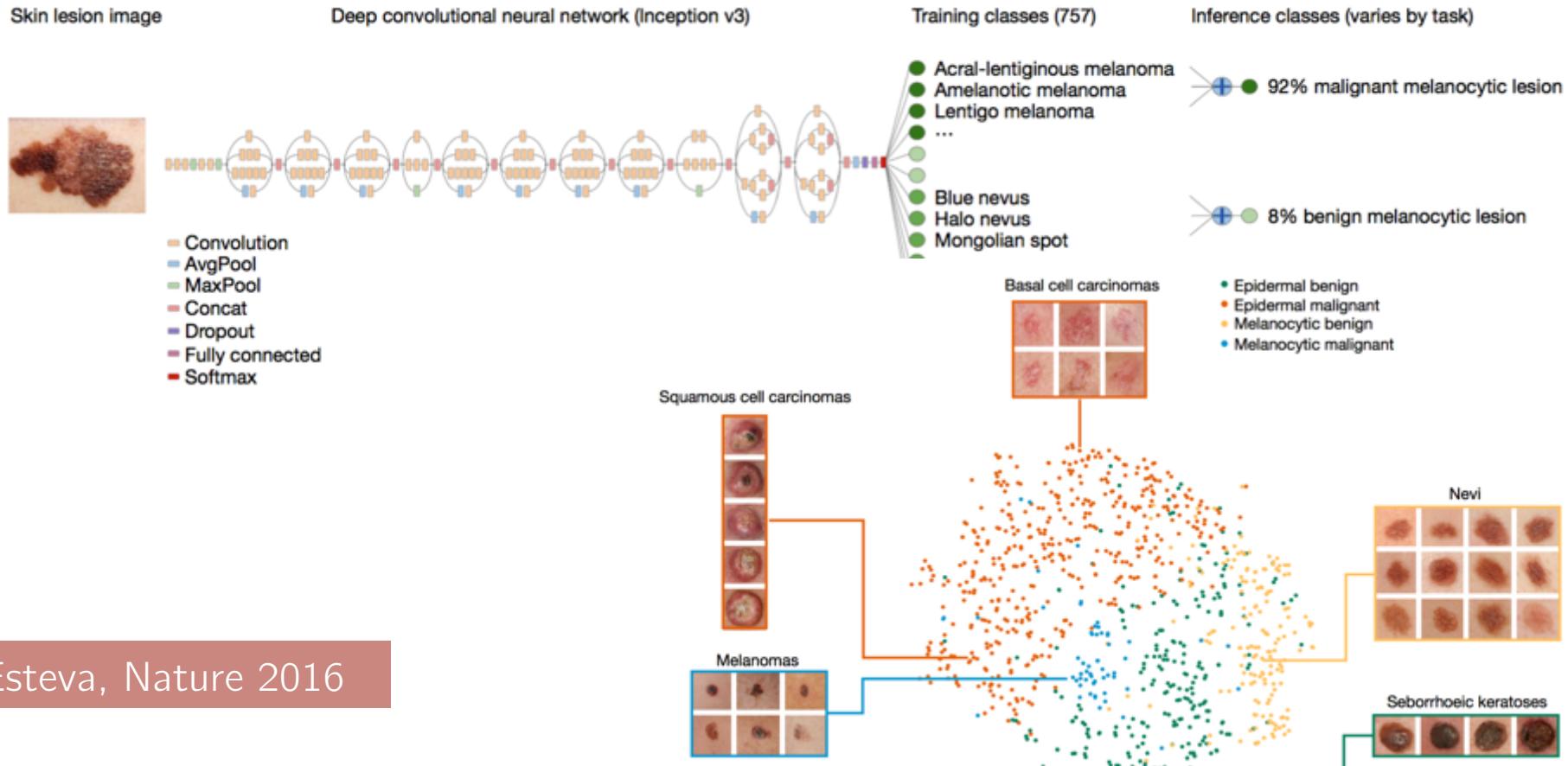
Varun Gulshan, PhD; Lily Peng, MD, PhD; Marc Coram, PhD; Martin C. Stumpe, PhD; Derek Wu, BS; Arunachalam Narayanaswamy, PhD; Subhashini Venugopalan, MS; Kasumi Widner, MS; Tom Madams, MEng; Jorge Cuadros, OD, PhD; Ramasamy Kim, OD, DNB; Rajiv Raman, MS, DNB; Philip C. Nelson, BS; Jessica L. Mega, MD, MPH; Dale R. Webster, PhD



Medical Imaging

Dermatologist-level classification of skin cancer with deep neural networks

Andre Esteva^{1*}, Brett Kuprel^{1*}, Roberto A. Novoa^{2,3}, Justin Ko², Susan M. Swetter^{2,4}, Helen M. Blau⁵ & Sebastian Thrun⁶

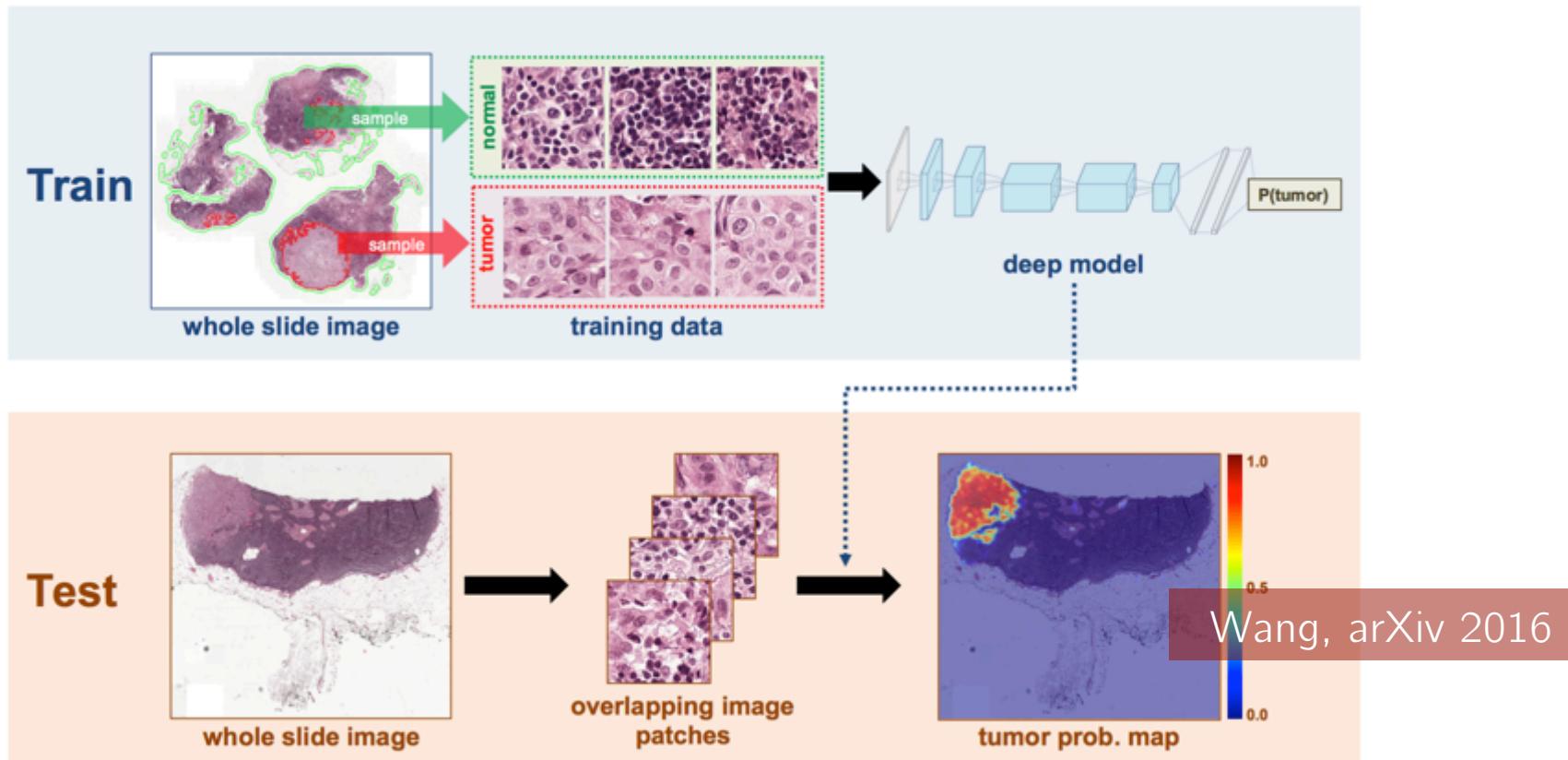


Esteva, Nature 2016

Medical Imaging

Deep Learning for Identifying Metastatic Breast Cancer

Dayong Wang Aditya Khosla* Rishab Gargya Humayun Irshad Andrew H Beck
Beth Israel Deaconess Medical Center, Harvard Medical School
*CSAIL, Massachusetts Institute of Technology



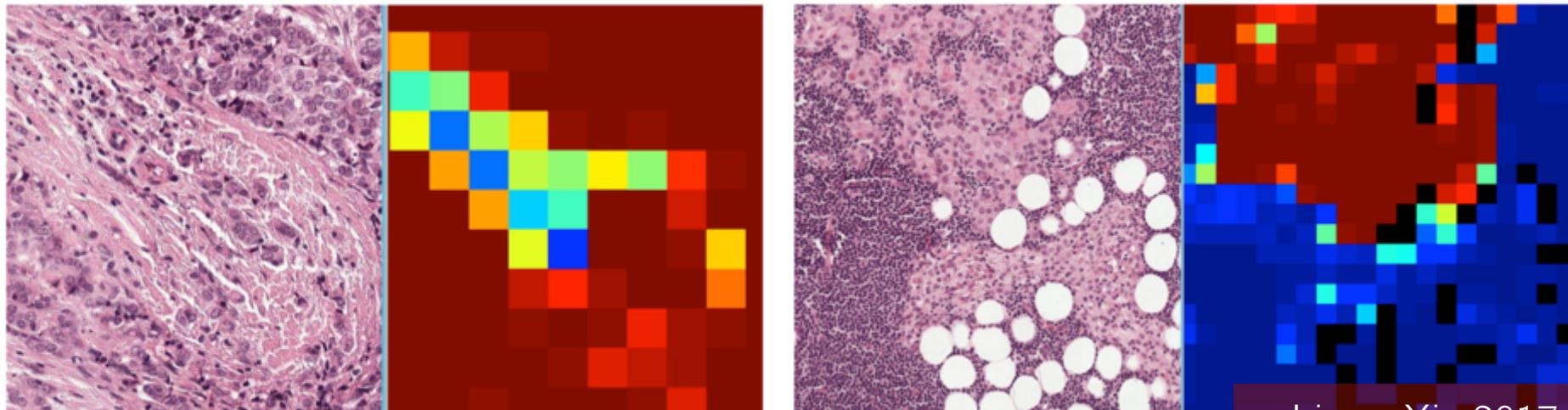
Medical Imaging

Detecting Cancer Metastases on Gigapixel Pathology Images

Yun Liu^{1*}, Krishna Gadepalli¹, Mohammad Norouzi¹, George E. Dahl¹,
Timo Kohlberger¹, Aleksey Boyko¹, Subhashini Venugopalan^{2**},
Aleksei Timofeev², Philip Q. Nelson², Greg S. Corrado¹, Jason D. Hipp³,
Lily Peng¹, and Martin C. Stumpe¹

{liuyun,mnorouzi,gdahl,lhpeng,mstumpe}@google.com

¹Google Brain, ²Google Inc, ³Verily Life Sciences,
Mountain View, CA, USA



Liu, arXiv 2017

Medical Text

Using Machine Learning to Parse Breast Pathology Reports

Adam Yala,¹ Regina Barzilay,¹ Laura Salama,³ Molly Griffin,² Grace Sollender,⁸ Aditya Bardia,¹⁰ Constance Lehman,⁵ Julliette M. Buckley,² Suzanne B. Coopey,² Fernanda Polubriaginof,⁹ Judy E. Garber,⁶ Barbara L. Smith,² Michele A. Gadd,² Michelle C. Specht,² Thomas M. Gudewicz,⁴ Anthony Guidi,⁷ Alphonse Taghian,³ and Kevin S. Hughes²

Pathology Report: REMOVED_ACCESSION_ID
ACCESSIONED ON: REMOVED_DATE
CLINICAL DATA: Carcinoma **right breast**.
*** FINAL DIAGNOSIS ***
LYMPH NODE (SENTINEL), EXCISION
(REMOVED_CASE_ID): METASTATIC CARCINOMA IN 1 OF 1 LYMPH NODE.
NOTE: The metastatic deposit spans 0.19cm and is identified on H&E and cytokeratin immunostains. A second cytokeratin-positive but cauterized focus likely also represents metastatic tumor (<0.1cm). There is **no evidence of extranodal extension**. BREAST (RIGHT), EXCISIONAL BIOPSY
(REMOVED_ACCESSION_ID : REMOVED_CASE_ID -B):
INVASIVE DUCTAL CARCINOMA (SEE TABLE #1). DUCTAL CARCINOMA IN-SITU, GRADE 1. ATYPICAL DUCTAL HYPERPLASIA. LOBULAR NEOPLASIA (ATYPICAL LOBULAR HYPERPLASIA).
TABLE OF PATHOLOGICAL FINDINGS #1 INVASIVE CARCINOMA
Tumor size: Cannot evaluate. Grade: 1.
Lymphatic vessel invasion: Not identified.
Blood vessel invasion: Not identified.
Margin of invasive carcinoma: Invasive carcinoma extends to less than 0.2cm from the inferior margin of the specimen.
Stains for receptors: Outside immunohistochemical stains demonstrate that the tumor cells express estrogen and progesterone receptors.



Name	Extraction
Breast Side	Right
Ductal Carcinoma in Situ	Present
Invasive Lobular Carcinoma	Absent
Invasive Ductal Carcinoma	Present
Cancer	Present
Lobular Carcinoma in Situ	Absent
Atypical Ductal Hyperplasia	Present
Atypical Lobular Hyperplasia	Present
Lobular Neoplasia	Present
Flat Epithelial Atypia	Absent
Blunt Adenosis	Absent
Atypia	Present
Positive Lymph Nodes	Present
Extracapsular Axillary Nodal Extension	Absent
Isolated Cancer Cells in Lymph Nodes	Absent
Lymphovascular Invasion	Absent
Blood Vessel Invasion	Absent
Estrogen Receptor Status	Positive
Progesterone Receptor Status	Positive
HER 2 (FISH) Status	Unknown

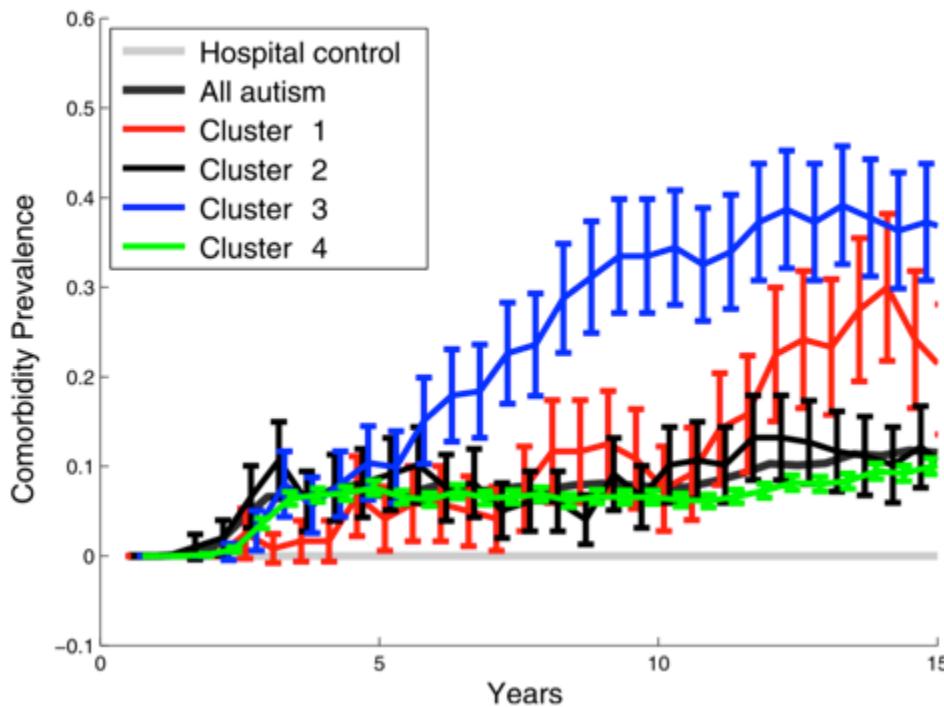
Category	Accuracy	F-score
Breast side	1.0	1.0
DCIS	.99	.99
ILC	.99	.99
IDC	1.0	1.0
Carcinoma	.94	.94
LCIS	1.0	.98
ADH	.90	.90
ALH	.98	.98
Lobular Neoplasia	.97	.97
Flat Epithelial Atypia	1.0	1.0
Blunt Adenosis	1.0	1.0
Atypia	.91	.91
Positive LN	.98	.98
ECE	.97	.97
ITC in LN	.96	.96
LVI	.92	.88
BVI	.93	.90
ER Status	.97	.97
PR Status	.97	.95
HER 2 Status	.96	.94
Report-Level	.90	N/A
Average	.97	.96

Yala, arXiv 2016

Comorbidity Clusters in Autism Spectrum Disorders: An Electronic Health Record Time-Series Analysis

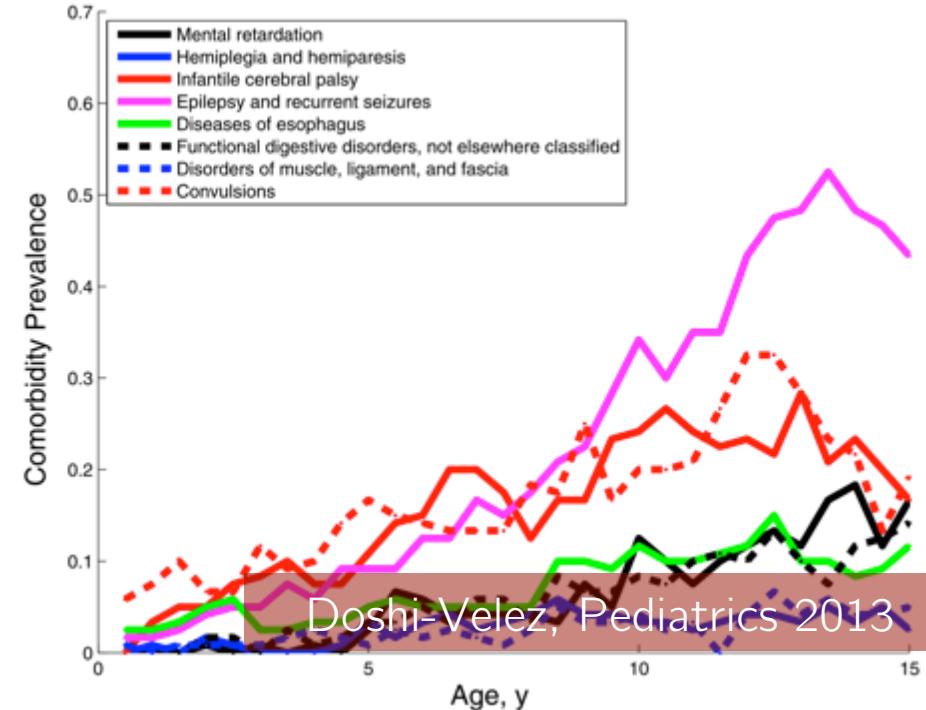
Structured Data

WHAT'S KNOWN ON THIS SUBJECT: Individuals with autism spectrum disorders have a higher comorbidity burden than the general pediatric population, including higher rates of seizures, psychiatric illness, and gastrointestinal disorders.



AUTHORS: Finale Doshi-Velez, PhD,^a Yaorong Ge, PhD,^b and Isaac Kohane, MD, PhD^a

^a*Center for Biomedical Informatics, Harvard Medical School, Boston, Massachusetts; and ^bCenter for Biomedical Informatics, Wake Forest University, Winston-Salem, North Carolina*



Cloud4Cancer Breast Cancer Detection

needle Aspirates to determine if a breast mass is malignant or benign. The current network is 99.11% sensitive to malignancy and 1.6 million trials demonstrate the worldwide hospital community. If you would like to contribute samples, please contact Brittany Wenger at cloud4cancerFNA@gmail.com.

Grand Prize Winner! Visit the [project site](#) for more information.

Breast FNA Decision Support by a High School Student!

Please enter the attributes of your FNA sample:

Clump Thickness	3, Cells are 80% mono-layered
Uniformity of Cell Size	3, Cells are 80% uniform
Uniformity of Cell Shape	2, Cells are 90% uniform
Marginal Adhesion	6, 50% Stick together
Single Epithelial Cell Size	9, Largest cells appear 90% larger
Bare Nuclei	4, 40% of nuclei have cytoplasm
Bland Chromatin	5, Chromatin is 50% coarse
Normal Nucleoli	4, 40% of nucleoli are abnormal
Mitoses	9, 90% mitotic activity appears abnormal

Send

Remote Procedure Call

Sending scenario to the Breast Cancer Cloud Service:
332694549

Server replies:
MALIGNANT

Close

<http://cloud4cancer.appspot.com/>

Achievement in Industry

- IBM Watson
 - Identify pulmonary embolism on CT
 - Detect abnormal wall motion on echocardiography
 - Watson Oncology in Japan, India, ...
- Enlitic
 - Fracture detection on radiographs
- DeepMind Health
 - High risk blood test detection/notification (Streams)
- Lumiata
- ...



106 STARTUPS TRANSFORMING HEALTHCARE WITH AI

Startups



https://cbi-blog.s3.amazonaws.com/blog/wp-content/uploads/2017/01/healthcare_AI_map_2016_1.png

Multimodal Data

eICU Collaborative Research Database



Data ↴

Community 💬

Code



Data ↴

Community 💬

Code

If you use MIMIC data or code in your work, please cite the following publication:

III, a freely accessible critical care database. Johnson AE, Shen L, Lehman L, Feng M, Ghassemi M, Moody B, Szoldad Mark RG. *Scientific Data* (2016). DOI: 10.1038/sdata.2016.35. Available from: <https://www.nature.com/articles/sdata201635> <http://mimic.physionet.org/> <http://eicu-crd.mit.edu/>

Multimodal Data

THE CANCER GENOME ATLAS



National Cancer Institute

National Human Genome Research Institute

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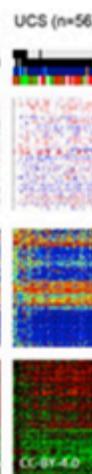
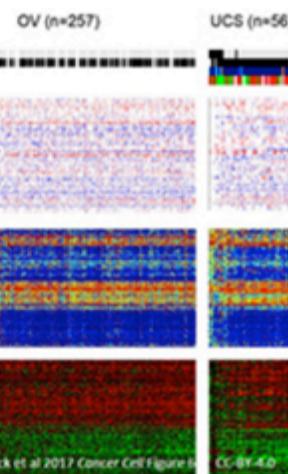
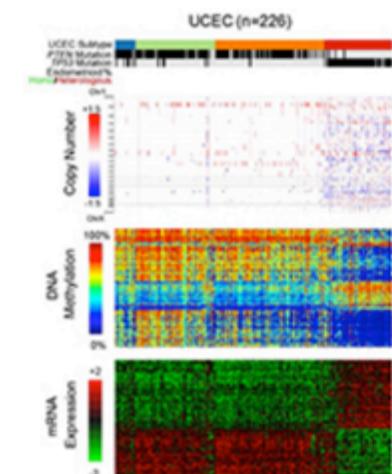
Cancers Selected for Study

Research Highlights

Publications

News and Events

About TCGA



TCGA Study of Uterine Carcinosarcoma

The Cancer Genome Atlas (TCGA) Research Network comprehensively characterized 57 uterine carcinosarcomas and found that these rare cancers share molecular features with both sarcomas and carcinomas.

[Learn More ▶](#)

Chernack et al 2017 *Cancer Cell* Figure 6

CC-BY-4.0



TCGA's Study
of Bile Duct
Cancer



TCGA study of
UCS



Cancers
Selected for
Study



About TCGA

TCGA in Action

News and Announcements

<https://cancergenome.nih.gov/>

Launch Data Portal

The Genomic Data Commons (GDC) Data Portal is an interactive data system for researchers to search, download, upload, and analyze harmonized cancer genomic data sets, including TCGA.

Questions About Cancer

Visit www.cancer.gov

Call 1-800-4-CANCER

Use [LiveHelp Online Chat](#)

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Images

Videos and Animations



FTP Service

The PMC FTP Service provides access to:

- file lists and files for the articles in the [PMC Open Access Subset](#);
- the [Author Manuscript Collection](#) and its file lists; and
- the [Historical OCR Collection](#).

The FTP service also allows users to [cross-reference PMC articles](#) with identifiers such as PubMed IDs, DOIs, and Manuscript IDs. Click on each of these collections and resources to learn more about the available files.

The directories available via the FTP service include:

- Open access individual article packages ([oa_package](#))
- Open access individual article PDFs ([oa_pdf](#))
- Open access bulk article packages ([oa_bulk](#))

<https://www.ncbi.nlm.nih.gov/pmc/tools/ftp/>

The National Library of Medicine presents MedPix®



MedPix® is a searchable online database of teaching cases and clinical topics, integrated with metadata including over 19,000 patient cases and 54,000 images. Our primary target audience includes physicians and nurses, allied health professionals, medical students and others.

The content material is organized by disease system, pathology category, patient profile, classification and captions. The collection includes keywords, image types, authors, and more.

In addition to searching and browsing images, the MedPix® website provides free AMA Category 1 CME credits online. Earn up to 30 minutes of CME with each case.

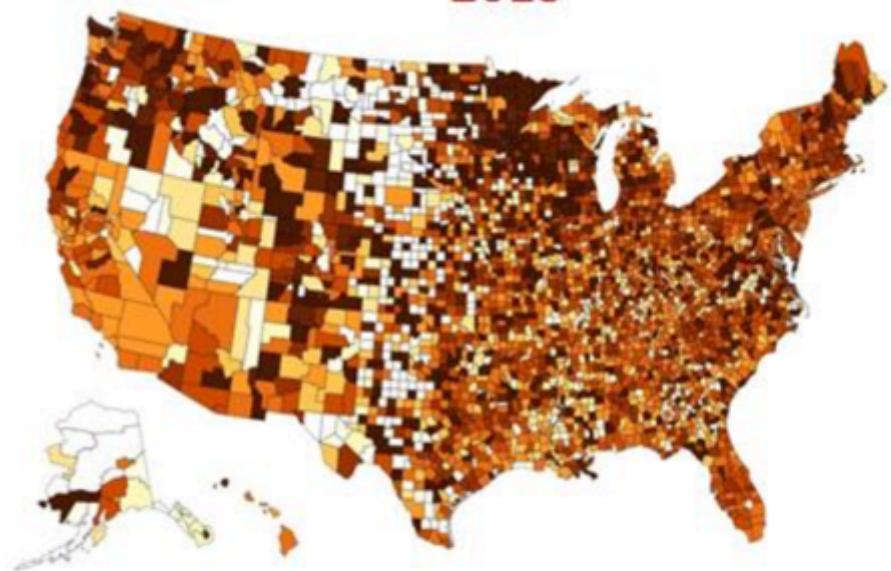
We are actively seeking new case contributions for the digital publication of MedPix® at the National Library of Medicine. Please join us in supporting one of the world's largest open-access teaching files.

Adoption of EHR

2008



2013



Courtesy by Owen Hsu (Wistron)



Standardization



1

Bitten by a turtle

W5921XS

2

Bitten by sea lion

W5611XD



3

Struck by macaw

W6112XA

Water Sports category

1st: Hit or struck by falling object due to accident to canoe or kayak – V9135XA

2nd: Civilian watercraft involved in water transport accident with military watercraft – V94810

3rd: Burn due to water-skis on fire – V9107XA

Strange Places category

 O1 → Hurt at the library Y92241

 O2 → Hurt at swimming pool of prison as the place of occurrence Y92146

 O3 → <https://www.linkedin.com/pulse/most-bizarre-icd-10-codes-infographic-nina-keller> Y92253

Democratization of Knowledge and Resources



coursera



TensorFlow



python™

Why Now?

- High quality (?) multimodal data
 - Variety, volume, velocity
 - Social media, sensor, wearable, vital signs, lab data, notes, imaging, -omics
 - Adoption of EHR
- Standardization
 - UMLS, SNOMED, ICD, RxNorm, LOINC, ...
- Advances and democratization in ML
 - Open-source / algorithms & tools
 - Different approaches of knowledge representation

Advantages

- Stability
- Consistency
- Can reduce
 - Medical cost
 - Healthcare inequality
 - Cognitive load
 - Computer vision, natural language processing, ...

Clinical Perspective

- Cost / Risk assessment and adjustment
 - Insurance
 - Resource redistribution
- Precision / Personalized medicine
 - For
 - Oncology / rare diseases / mental disorders / ...
 - Applications
 - Clinical decision support
 - Drug discovery
 - Outcome prediction
 - Lifespan prediction / Disease progression
 - Chronic disease management
 - Early prediction of blood glucose for self-management

CS/AI/ML Perspective

- Risk stratification
- Causal inference
- Bias
- Time-series
- Unstructured data
- Interpretability
- Disease progression modeling
- Reasoning and decision making

Issues

- Domain specific vs. generalization
- Data quality
- Privacy / Data security
 - Open-source and ubiquitous
 - Innovation, ecosystem
- Transparency

THIS IS YOUR MACHINE LEARNING SYSTEM?

YUP! YOU POUR THE DATA INTO THIS BIG
PILE OF LINEAR ALGEBRA, THEN COLLECT
THE ANSWERS ON THE OTHER SIDE.

WHAT IF THE ANSWERS ARE WRONG?

JUST STIR THE PILE UNTIL
THEY START LOOKING RIGHT.



Replacing Your Job?

The world's first artificially intelligent lawyer was just hired at a law firm



Chris Weller

© May 16, 2016, 10:26 AM 44,723

FACEBOOK

LINKEDIN

TWITTER

EMAIL

PRINT

Lawyers can get a bad reputation for being slimy and conniving, but ROSS has neither of those qualities.

Ask ROSS to look up an obscure court ruling from 13 years ago, and ROSS will not only search for



<http://www.businessinsider.com/the-worlds-first-artificially-intelligent-lawyer-gets-hired-2016-5>

Limitations of AI

- Weak AI vs. Strong AI / Superintelligence
- Computational intelligence \neq computational consciousness
- Procedure
- Emotion
- Thinking, reasoning and decision making
 - Inference
 - Abstraction
 - Cognition
 - Commonsense knowledge
 - Insight

A golden retriever dog is sitting at a desk in a laboratory setting. The dog is wearing black safety goggles and a white lab coat over its brown fur. It has a small "DANGER! HOT SURFACE" label pinned to its coat. In front of the dog is a blue mug with the words "PICK ONE" and "NATURE'S RA..." visible. To the right of the dog is a round-bottom flask containing a brown liquid, connected to a glass apparatus. The background is a purple wall.

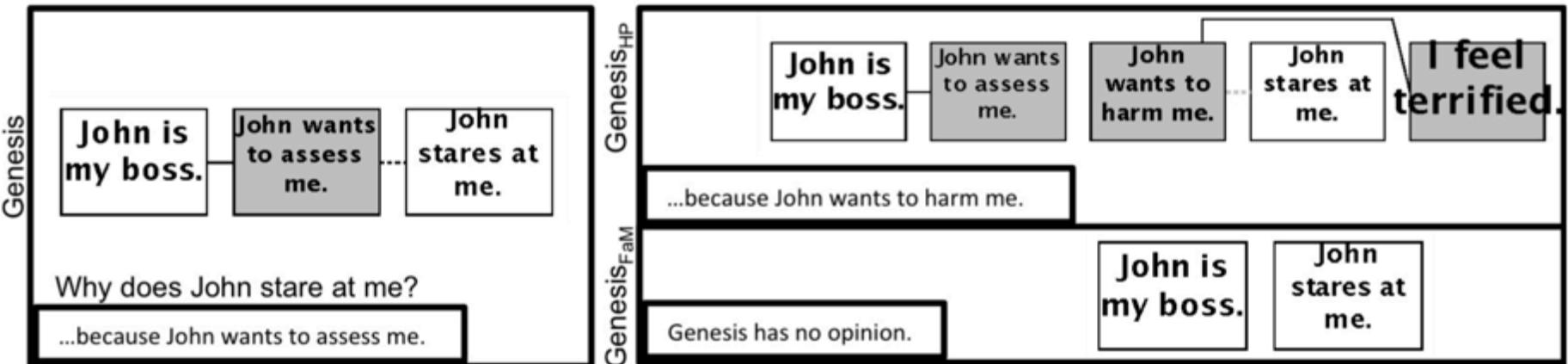
I HAVE NO
IDEA WHAT
I'M DOING

[http://knowyourmeme.com/photos/
234739-i-have-no-idea-what-i-m-doing](http://knowyourmeme.com/photos/234739-i-have-no-idea-what-i-m-doing)

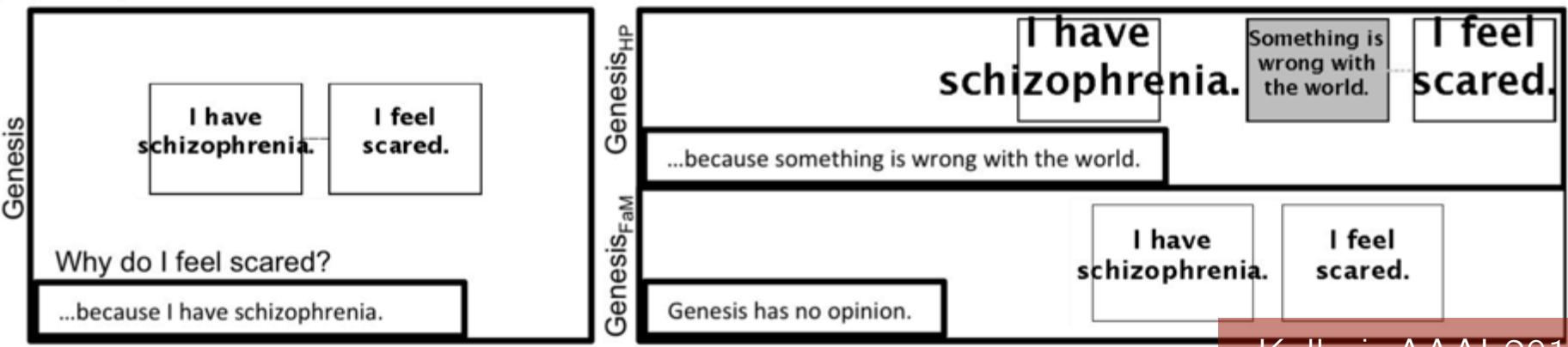
Inducing Schizophrenia in an Artificially Intelligent Story-Understanding System

Pratyusha Kalluri and Patrick Henry Winston

(B) System performance on the Paranoid Delusion Task



(C) System performance on the Persistence of Delusion Task



- Not replace, but may change significantly
- *It was the best of times, it was the worst of times*

A Tale of Two Cities
Charles Dickens



VIEWPOINT

INNOVATIONS IN HEALTH CARE DELIVERY

Adapting to Artificial Intelligence Radiologists and Pathologists as Information Specialists

Artificial intelligence—the mimicking of human cognition by computers—was once a fable in science fiction but is becoming reality in medicine. The combination of big data and artificial intelligence, referred to by some as the fourth industrial revolution,¹ will change radiology and pathology along with other medical specialties. Although reports of radiologists and pathologists being replaced by computers seem exaggerated,² these specialties must plan strategically for a future in which artificial intelligence is part of the health care workforce.

Radiologists have always revered machines and tech-

This progress in radiologists. Radiology ages, such as chest radi complex and data rich. Cr and magnetic reson greater clarity, has m stances; for example, a chest radiograph but Jha, JAMA 2016 has come at a price— markedly. For example, 4000 images in a CT

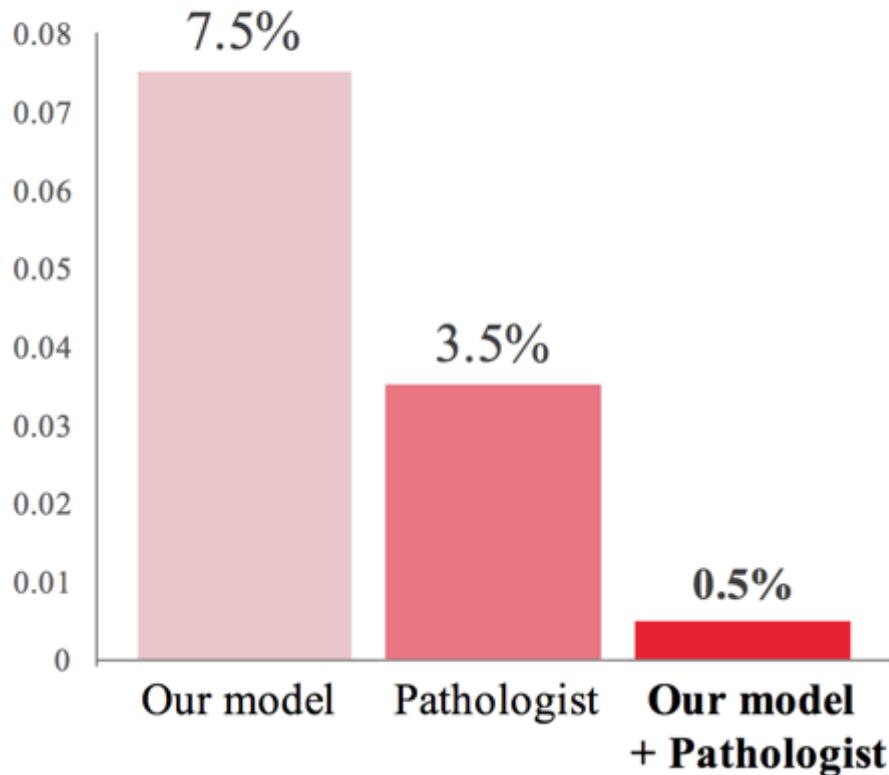
Saurabh Jha, MBBS,
MRCS, MS
Department of
Radiology, University
of Pennsylvania,
Philadelphia.

Eric J. Topol, MD
Scripps Research
Institute, La Jolla,
California.

What We Can Do

- Find good problems, collect reliable data > Big data and algorithms
- Collaboration > Expert or AI only
 - Expert: high-level integration, interpretation and decision making (learn Bayesian logic, statistics, and data science and be aware of other sources of information!)
 - AI: pattern recognition and massive repetitive tasks
- Sharing
 - AI researchers open-source platforms and algorithms
 - You can open-source data and knowledge
 - We can do nothing without sharing!
- Experience
 - Learning from AI
 - Communicating with AI

Deep Learning vs Pathologist



The **combination** of a pathologist and the Beck Lab deep learning system **reduces error rate by 85% to 0.5%.**

Courtesy by Dr. Andrew Beck (PathAI)

Take Home Message

- Data-driven, machine learning-based approach
- Define good problems and find reliable data sources
 - Cost, risk, precision medicine
 - Causality, bias, unstructured data, interpretability, reasoning and decision making
- Human-machine collaboration
- Share your data and knowledge
- Learn from / communicate with AI
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- ckbjimmy@mit.edu / Wei-Hung Weng (LinkedIn)