Artificial Intelligence in Medicine

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CLINICAL + TRANSLATIONAL SCIENCE INSTITUTE

Artificial Intelligence (AI)

- "General AI" – goal is to create intelligent machines that can successfully perform any intellectual task that a human being can.
- "Narrow AI" – goal is to create software or computing resource that can accomplish specific problem solving or reasoning tasks.
- The field of AI field draws upon computer science, computer engineering, mathematics, statistics, psychology, linguistics, philosophy, and neuroscience.

"Narrow AI" has been quite successful.

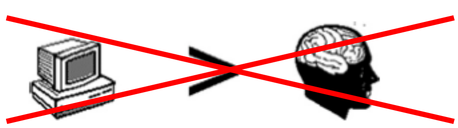
"Some of the most successful applications of AI are those in which the AI is spread like raisins in a loaf of raisin bread: the raisins do not occupy much space, but they often provide the principle source of nutrition." *

* Esther Dyson, Industrial analyst

The Fundamental Theorem of Biomedical Informatics

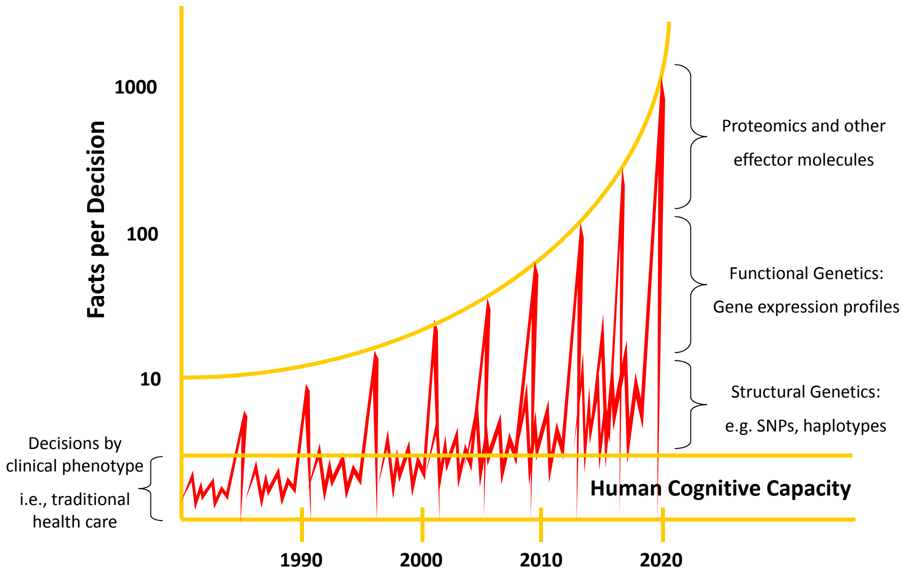
- A person working with a computing resource (e.g., AI) is better than that same person unassisted.

- Not



Friedman CP. A 'fundamental theorem' of biomedical informatics. J Am Med Inform Assoc. 2009 Mar-Apr; 16(2): 169–170.

Limitations of Human Cognitive Capacity



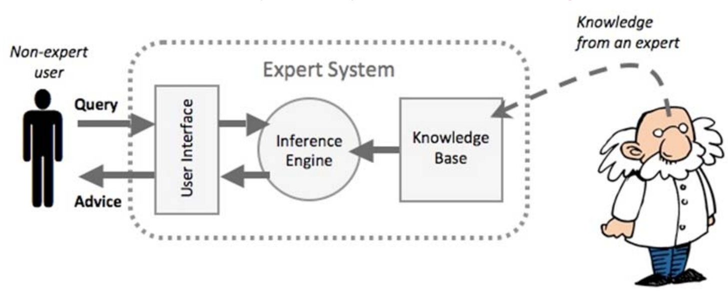
William Stead, IOM Meeting, October 8, 2007. Growth in factors affecting provider decisions versus human cognitive capacity.

Selected Areas of Artificial Intelligence

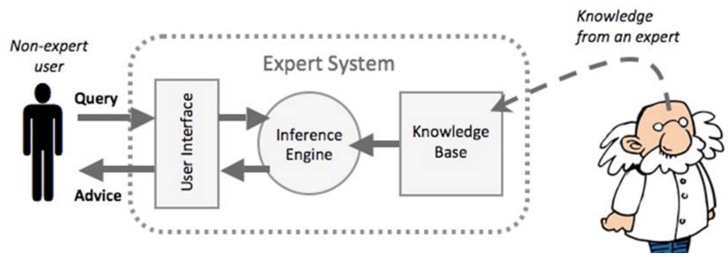
- Knowledge Representation and Reasoning
  - methods to represent large amounts of knowledge efficiently and effectively, to enable reasoning and decision making
- Search and Optimization
  - Methods for finding optimal solutions to highly complex problems
- Natural Language Processing
  - methods for human-computer interaction through natural text and speech
- Machine Learning
  - analysis of data and trends. Training of system(s) to learn from data and trends to enable system to make decisions

AI in Clinical Medicine: Cognitive Support

Medical Expert Systems for Diagnosis



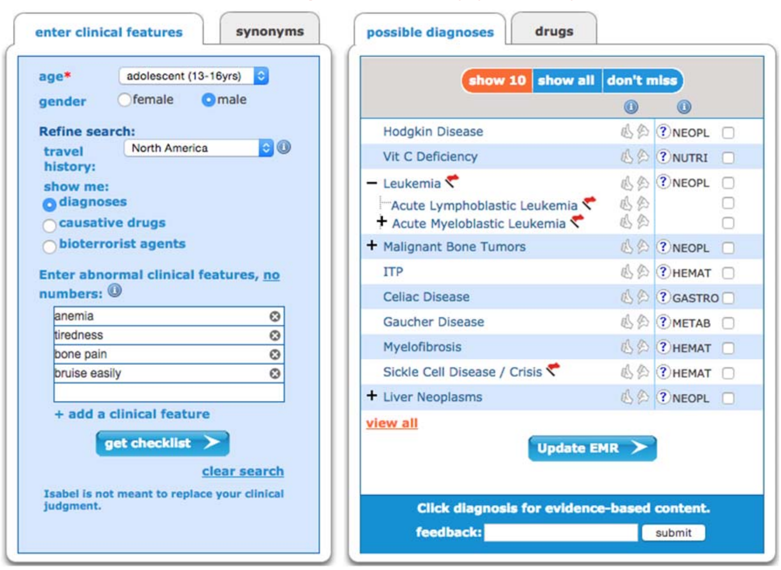
Medical Expert Systems for Diagnosis



Variable and Sample Used*	DXPLAIN	ILIAD	MEDITEL	QMR
	mean (95 percent confidence interval)			
Diagnosis in Knowledge Base	0.91 (0.86–0.97)	0.76 (0.68–0.85)	0.85 (0.78–0.92)	0.73 (0.65–0.82)
Correct Diagnosis				
105 cases	0.69 (0.60–0.78)	0.61 (0.52–0.70)	0.71 (0.62–0.79)	0.52 (0.43–0.62)
63 cases	0.79 (0.69–0.90)	0.76 (0.65–0.87)	0.89 (0.81–0.97)	0.71 (0.60–0.83)
Rank‡				
Diagnosis in program studied§	12.4 (9.5–15.3)	10.4 (8.0–12.8)	13.3 (10.5–16.1)	6.6 (3.0–10.3)
Diagnosis in all four programs¶	11.7 (8.3–15.1)	10.2 (7.5–12.9)	12.0 (8.8–15.3)	5.4 (3.7–7.1)

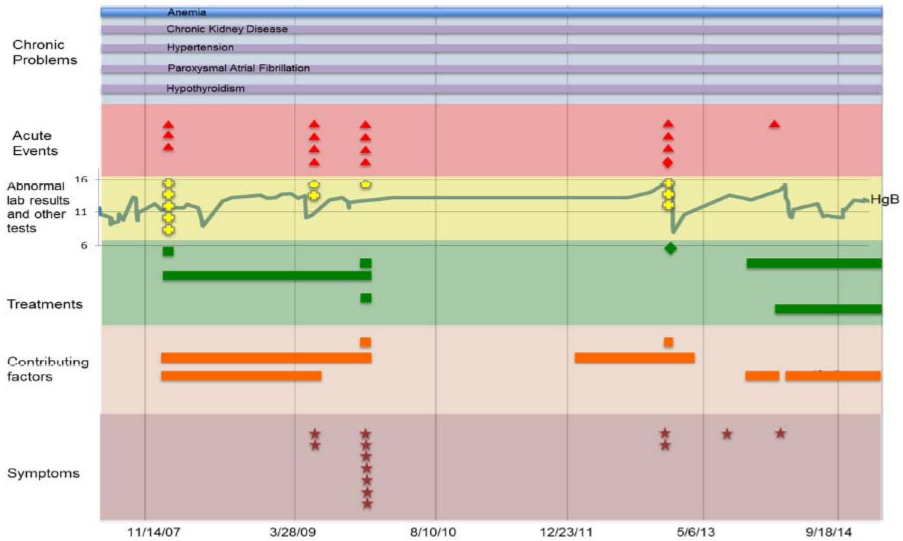
Berner ES, Webster GD, et al. Performance of four computer-based diagnostic systems. N Engl J Med. 1994 Jun 23;330(25):1792-6.

Isabel: A Diagnostic Support System



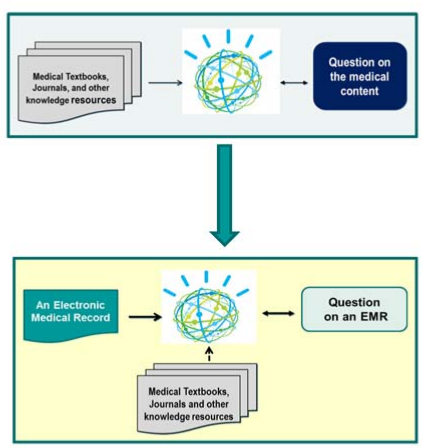
Henderson EJ, Rubin GP. The utility of an online diagnostic decision support system (Isabel) in general practice: a process evaluation. JRSM Short Rep. 2013 Apr 4;4(5):31.

Problem-Oriented Patient Record Summarization: Anemia



Devarakonda, M. Watson cognitive computing for Electronic Medical Records. AMIA Joint Summits 2016.

Question Answering on a Patient Record



Devarakonda, M. Watson cognitive computing for Electronic Medical Records. AMIA Joint Summits 2016.

Question Answering on a Patient Record

Why was *Sitagliptin* stopped?

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:td65 year old male

Wants to discuss the results of the MRI - has anteros
Also results of his labs.

He was unable to get Januvia - he is not on it.
Cost is also very expensive
His DM control is improved -
Will hold off starting it at this point
Has lost about 6-8 lb since last time as he is doing
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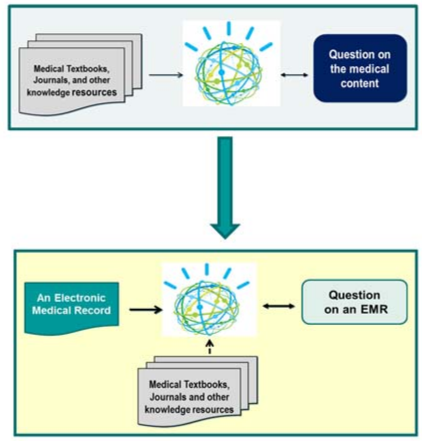
Question Type	Num. of questions	Example
yes/no	91	Is the substance abuse problem ongoing or resolved?
what	53	What are the results of the urine tox screen?
temporal-when	17	When was non-insulin-dependent diabetes mellitus diagnosed?
reason - why, how	16	Why did he get malignant tumor of colon at this age?



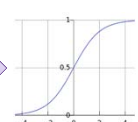
Raghavan, P, Patwardhan, S. Question answering on Electronic Medical Records. AMIA Joint Summits on Translational Science, Podium Presentation, 2016.

Learning Electronic Medical Record (LEMR) System

Observe and store
EMR usage patterns

Training data
- patient data
- usage patterns

Machine learning

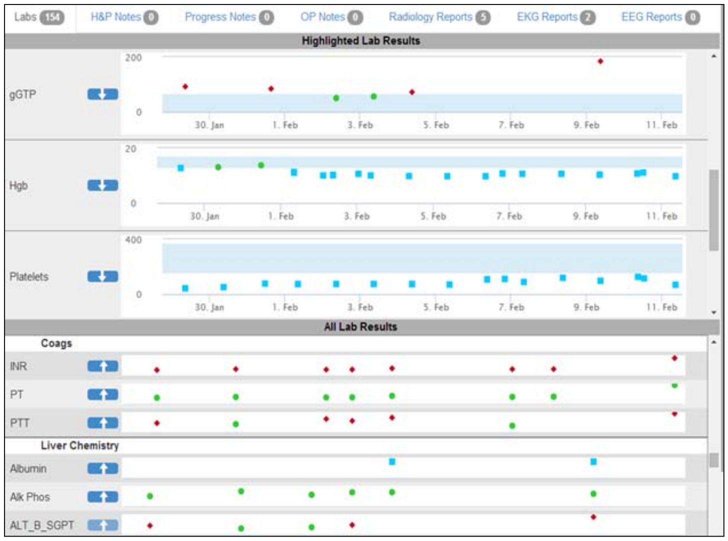


Apply models to a patient case

EMR display adapted to represent predicted usage

King AJ, Cooper GF, Hochheiser H, Clermont G, Visweswaran S. Development and preliminary evaluation of a prototype of a Learning Electronic Medical Record System. AMIA Annu Symp Proc. 2015 Nov 5;2015:1967-75.

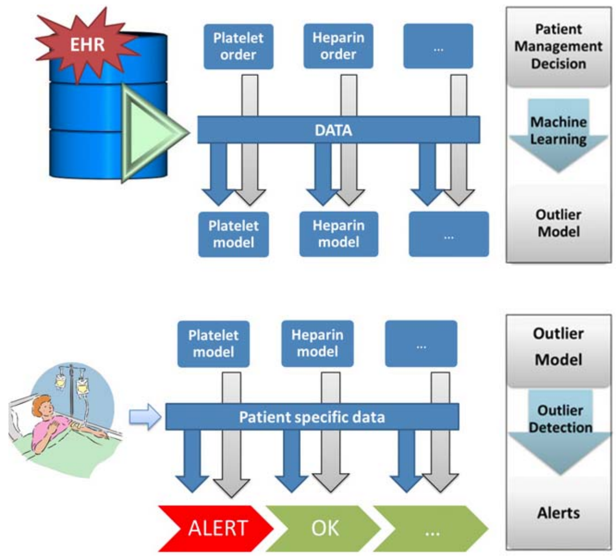
Learning Electronic Medical Record System



King AJ, Cooper GF, Hochheiser H, Clermont G, Visweswaran S. Development and preliminary evaluation of a prototype of a Learning Electronic Medical Record System. AMIA Annu Symp Proc. 2015 Nov 5;2015:1967-75.

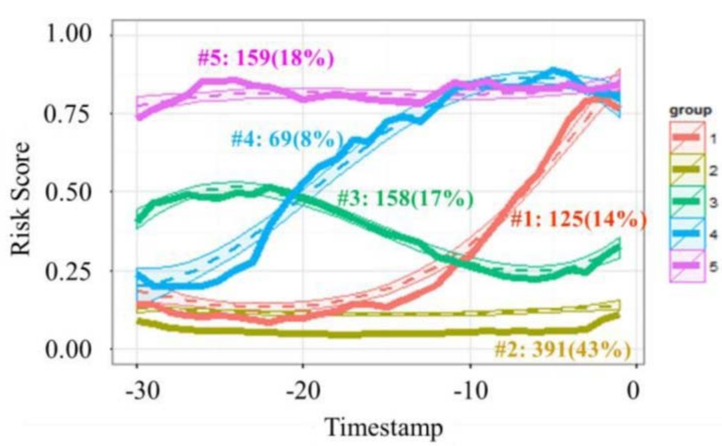
AI in Clinical Medicine: Safety Net

Learning to Detect Outliers in Healthcare Delivery



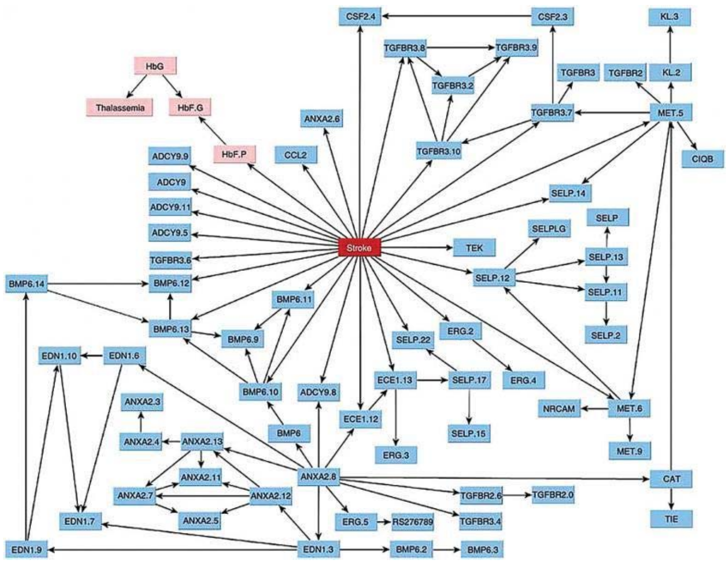
Hauskrecht M, Batal I, Valko M, Visweswaran S, Cooper GF, Clermont G. Outlier detection for patient monitoring and alerting. J Biomed Inform. 2013 Feb;46(1):47-55.

Early Warning Scoring System to Alert Risk of Developing Cardio-Respiratory Instability



Chen L, Dubrawski A, Clermont G, Hravnak M, Pinsky MR. Modelling risk of cardio-respiratory instability as a heterogeneous process. AMIA Annu Symp Proc. 2015 Nov 5;2015:1841-50.

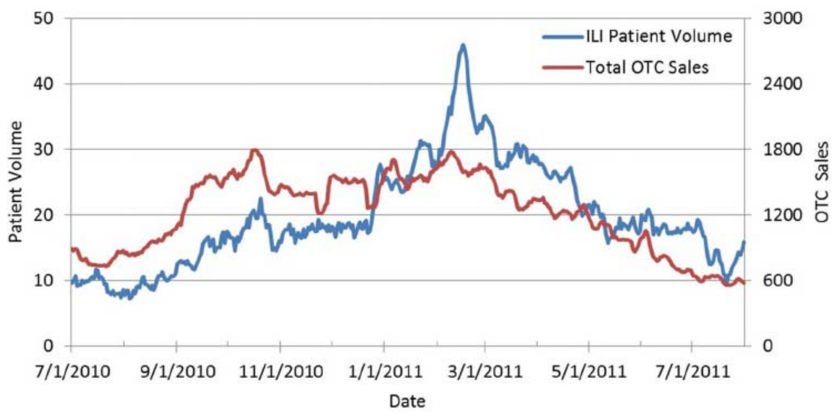
Predicting Stroke Risk in Sickle Cell Anemia from Genomics



Sebastiani P, Ramoni MF, et. al. Genetic dissection and prognostic modeling of overt stroke in sickle cell anemia. Nature genetics. 2005;37(4):435-440.

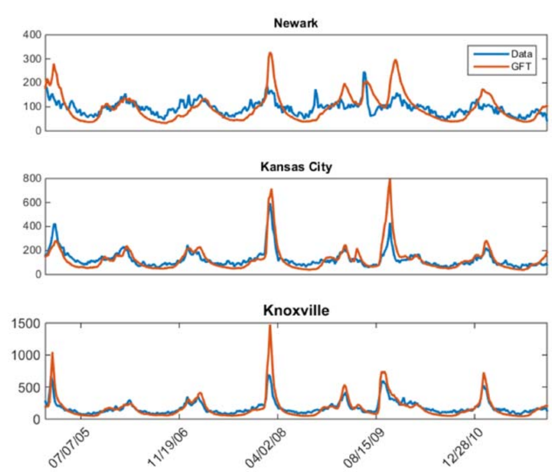
AI in Population Health

Real-time Outbreak and Disease Surveillance from Sales of Over-the-Counter (OTC) Healthcare Products



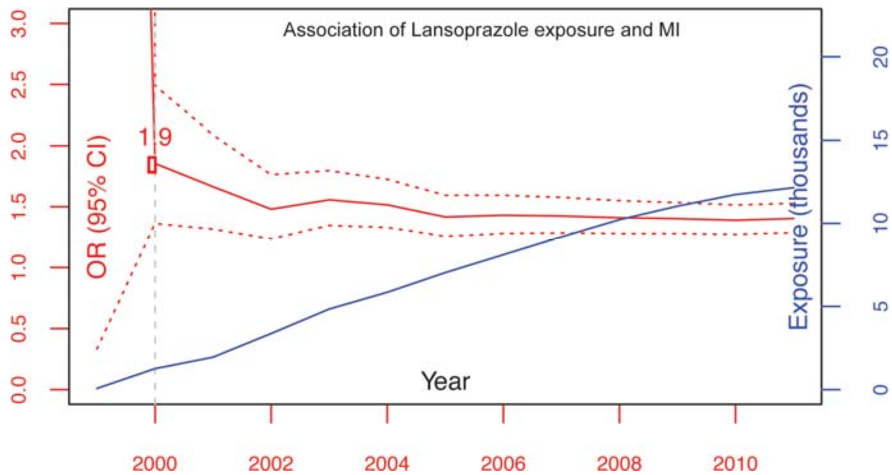
Wagner MM, Robinson JM, Tsui FC, Espino JU, Hogan WR. Design of a national retail data monitor for public health surveillance. J Am Med Inform Assoc. 2003 Sep-Oct;10(5):409-18.

Disease Surveillance Using Internet Search Queries



Klembczyk, JJ, Jalalpour, M, et. al. Google flu trends spatial variability validated against Emergency Department influenza-related visits. J Med Internet Res. 2016 Jun; 18(6): e175.

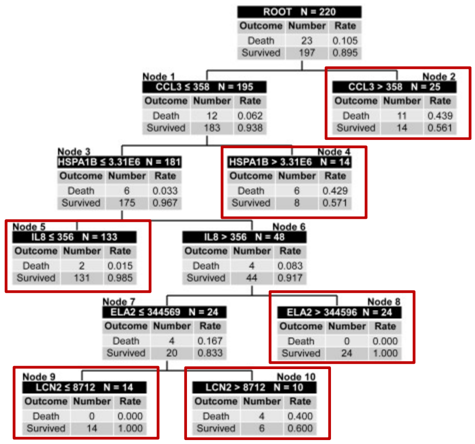
Pharmacovigilance Using Data-Mining of Electronic Medical Record data



Shah NH, LePendu P, et. al. Proton pump inhibitor usage and the risk of myocardial infarction in the general population. PLoS One. 2015 Jun 10;10(6):e0124653.

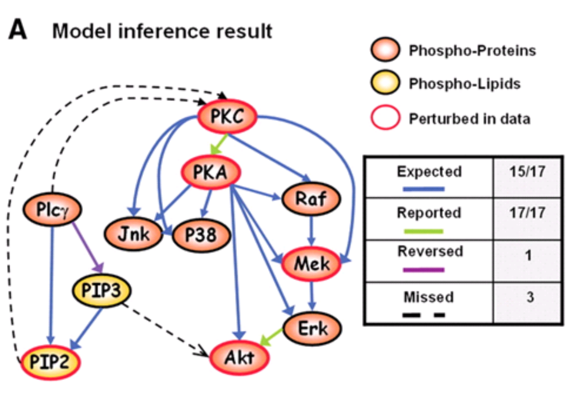
AI in Biomedical Research

Risk Subtyping in Pediatric Sepsis Using a Classification Tree Model



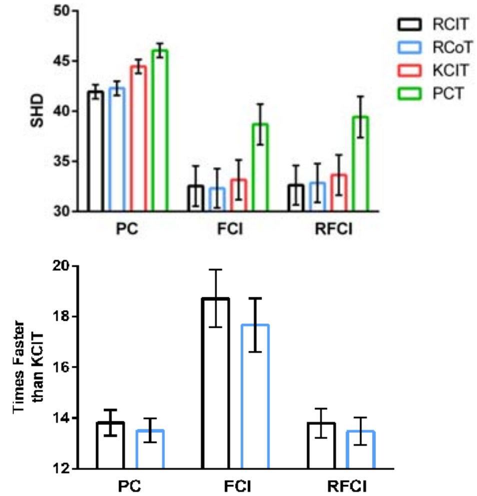
Wong HR et al. The pediatric sepsis biomarker risk model. Crit Care. 2012 Oct 1;16(5):R174.

Learning Causal Networks From Data



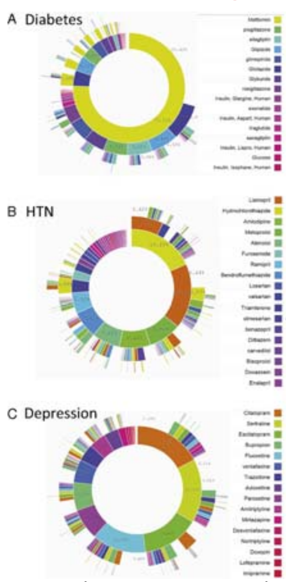
Sachs K, Perez O, Pe'er D, Lauffenburger DA, Nolan GP. Causal protein-signaling networks derived from multiparameter single-cell data. Science. 2005 Apr 22;308(5721):523-9.

Speeding Up Causal Discovery Algorithms



Strobl, EV, Zhang, K, Visweswaran, S. Approximate kernel-based conditional independence tests for fast non-parametric causal discovery. arXiv:1702.0387, 2017.

Large Scale Data Mining of EHR Data



Hripcsak G, Ryan PB, et. al. Characterizing treatment pathways at scale using the OHDSI network. Proc Natl Acad Sci U S A. 2016 Jul 5;113(27):7329-36.

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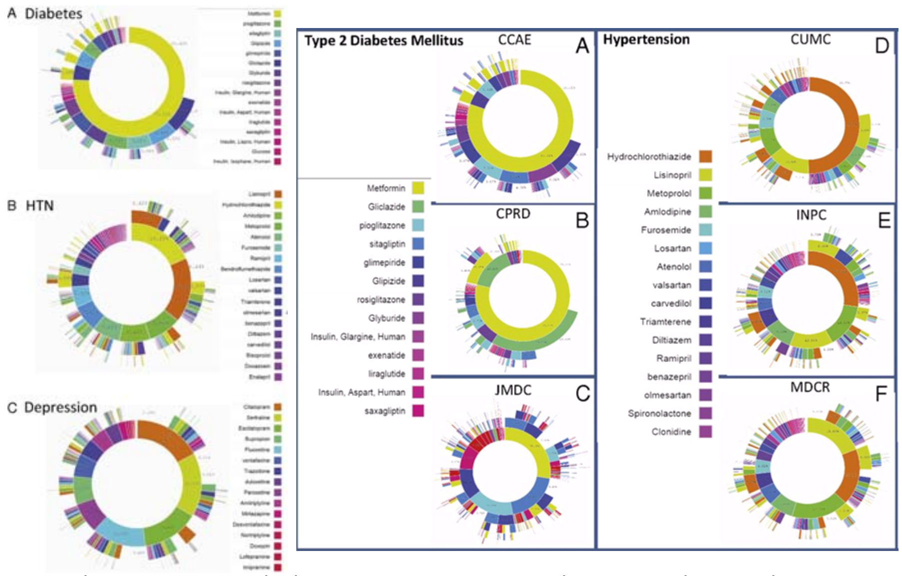

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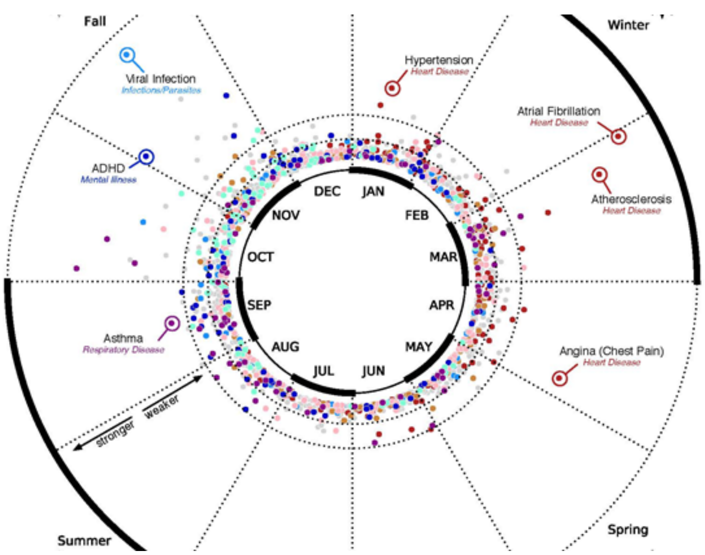
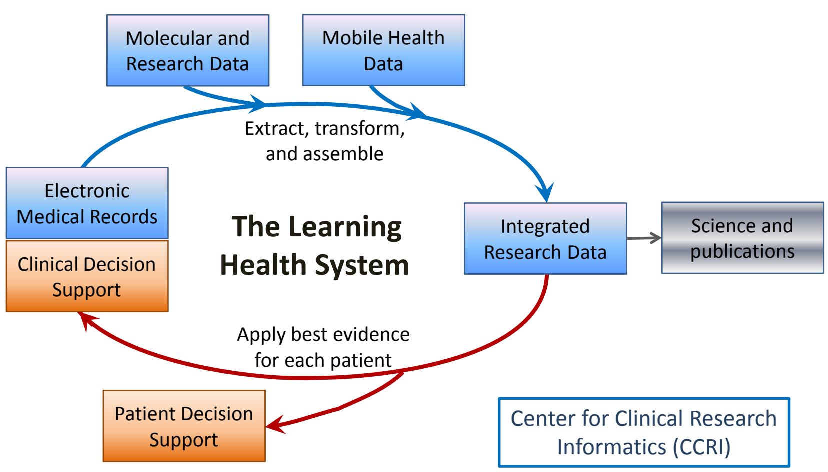


Boland MR, Shahn Z, Madigan D, Hripcsak G, Tatonetti NP. Birth month affects lifetime disease risk: a phenome-wide method. J Am Med Inform Assoc. 2015 Sep;22(5):1042-53.

Learning Health System

Learning Health System (LHS)



Friedman CP, Wong AK, Blumenthal D. Achieving a nationwide learning health system. Sci Transl Med. 2010 Nov 10;2(57):57cm29.
See http://www.ccri.thevislab.com

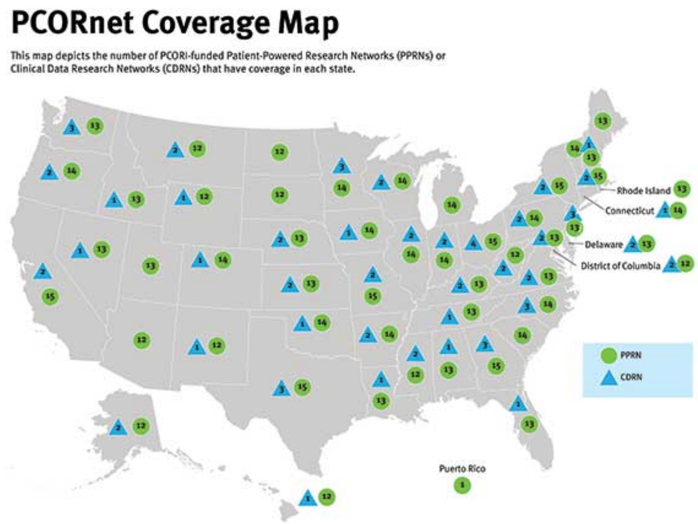
Example: Data-Enabled Physician Support

- Dr. Lilia is seeing John, who is on metformin for type 2 diabetes. John’s HbA1c remains high, so Dr. Lilia must modify John’s drug therapy.
- Options include increasing the dose of metformin or switching to one of four second-line medications: sulfonylurea, sitagliptin, canagliflozin, or insulin.
- However, no professional guidelines or published studies offer an answer in the context of John who has several co-morbidities including hypertension and sickle-cell anemia.
- Dr. Lilia accesses an application that identifies a cohort of patients with characteristics similar to John (“Patients Like Mine”), analyzes the effect of each medication on reducing HbA1c in this cohort, and returns a ranked list of medication options and outcomes.

Example: Data-Enabled Patient Self-Management

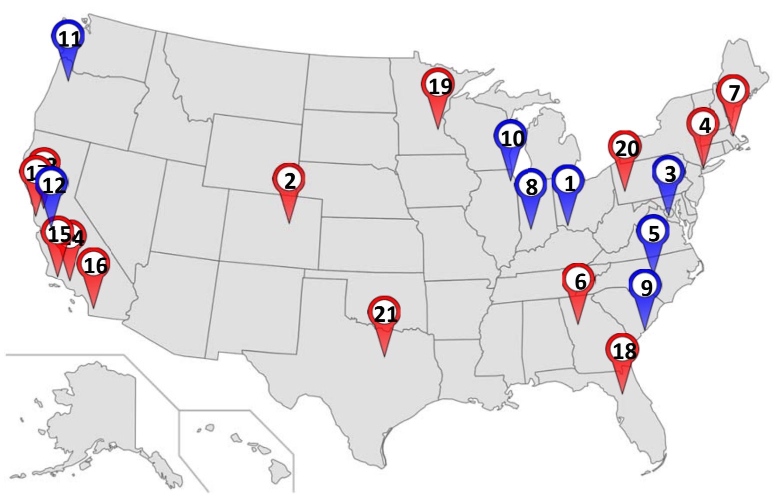
- Joe is a 40-year old man with type 2 diabetes. A key goal in managing his diabetes is modulating the rise in glucose levels after a meal by regulating what and how much he eats.
- John’s physician prescribes a smartphone app and wearable activity monitor that predicts the post-meal rise in glucose level using a predictive model that considers a range of parameters that include John’s age, ethnicity, anthropometrics (height, weight, BMI, body fat distribution), carbohydrate intake, meal times, physical activity, sleep-wake cycle, lifestyle, medications, and gut microbiome and genome.
- Accurate prediction of glycemic response is enabled by a predictive model that is trained using a cohort of patients with type 2 diabetes.

Federated EHR Data Network: PCORI-funded PCORnet



13 Clinical Data Research Networks (CDRNs), and 21 Patient-Powered Research Networks (PPRNs) cover 150 conditions ; ~110 million patients. See http://pcornet.org/

Federated EHR Data Network: NIH-funded ACT Network



21 CTSA sites; to expand to all 60+ CTSA sites; 40 million patients.
See http://www.act-network.org/

Precision Medicine Initiative

"My hope is that this becomes the foundation, the architecture, whereby in 10 years from now we can look back and say that we have revolutionized medicine."

- PRESIDENT BARACK OBAMA

Precision Medicine Initiative

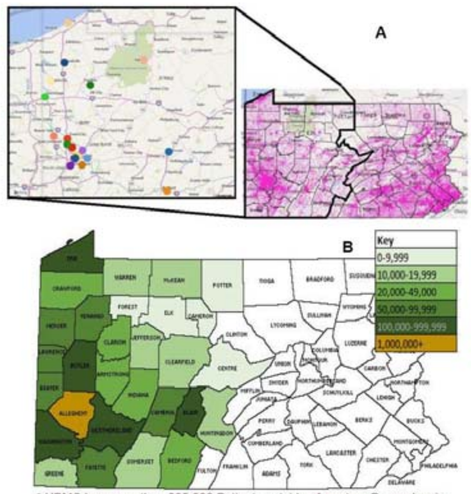
- One million+ participants, reflecting the broad diversity of the U.S.
- Data
  - Participant questionnaires
  - Electronic health records
  - A baseline physical evaluation
  - Biospecimens (blood and urine samples)
  - Genomic sequences
  - Mobile/wearable technologies
  - Geospatial/environmental data
- Data shared freely and fast to inform a variety of research studies

See https://www.nih.gov/allofus-research-program

All of Us Research Program (All of Us PA)

All of Us Pennsylvania

All of Us Research Program



* UPMC has more than 225,000 Patients outside of western Pennsylvania.

The Al of Us PA project will enroll 100,000 participants for the All of Us Research Program and will collect EHR data and bio specimens.

PIs: Steven E. Reis (CTSI) , Shyam Visweswaran (Biomedical Informatics) and Oscar Marroquin (Medicine)

Thank you

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http://www.thevislab.com