Health Informatics

Lecture 1: Introduction

Samantha Kleinberg
samantha.kleinberg@stevens.edu

About me: Samantha Kleinberg

- PhD in CS
- Have worked in biomathematics, bioinformatics/computational biology, biomedical informatics
- Current research
  - Time series data, causal inference
  - Simulation
  - Mobile health

NICU dataset

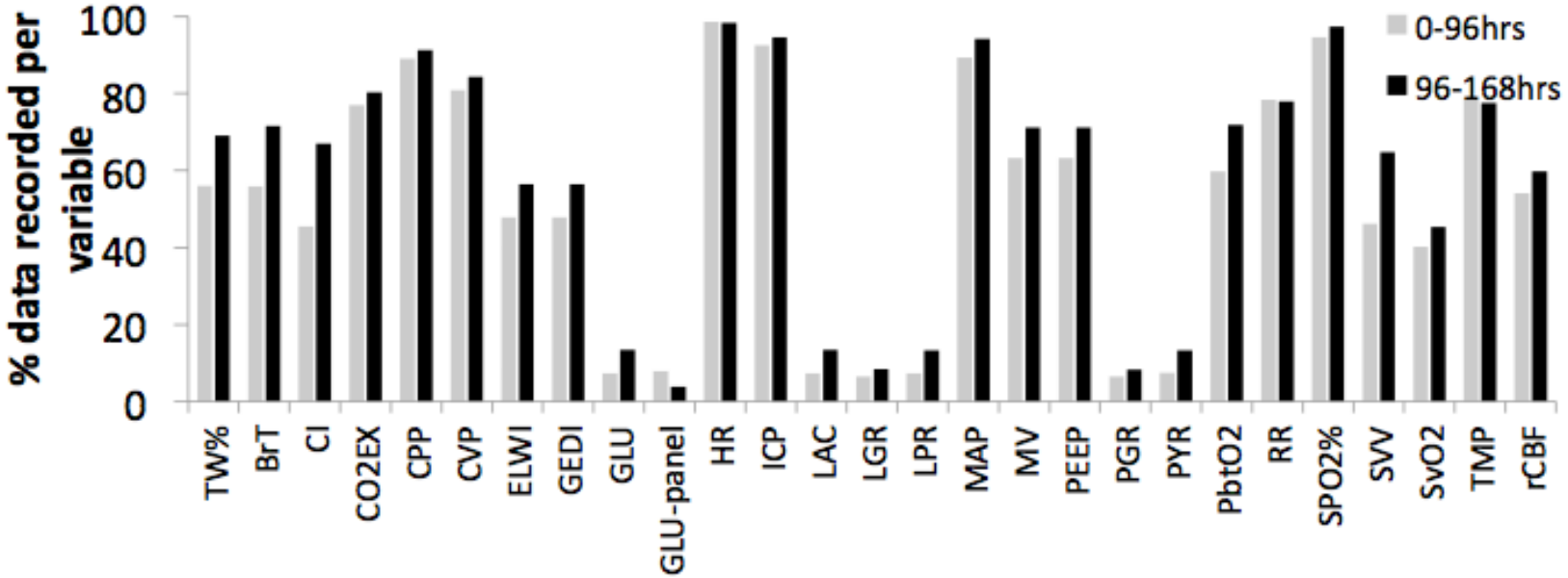
- 98 patients with subarachnoid hemorrhage

- Monitoring included
  - Depth and surface EEG
  - Microdialysis
  - Physiologic measurements

  (no data on procedures)

Lots of data, but lots of missing data

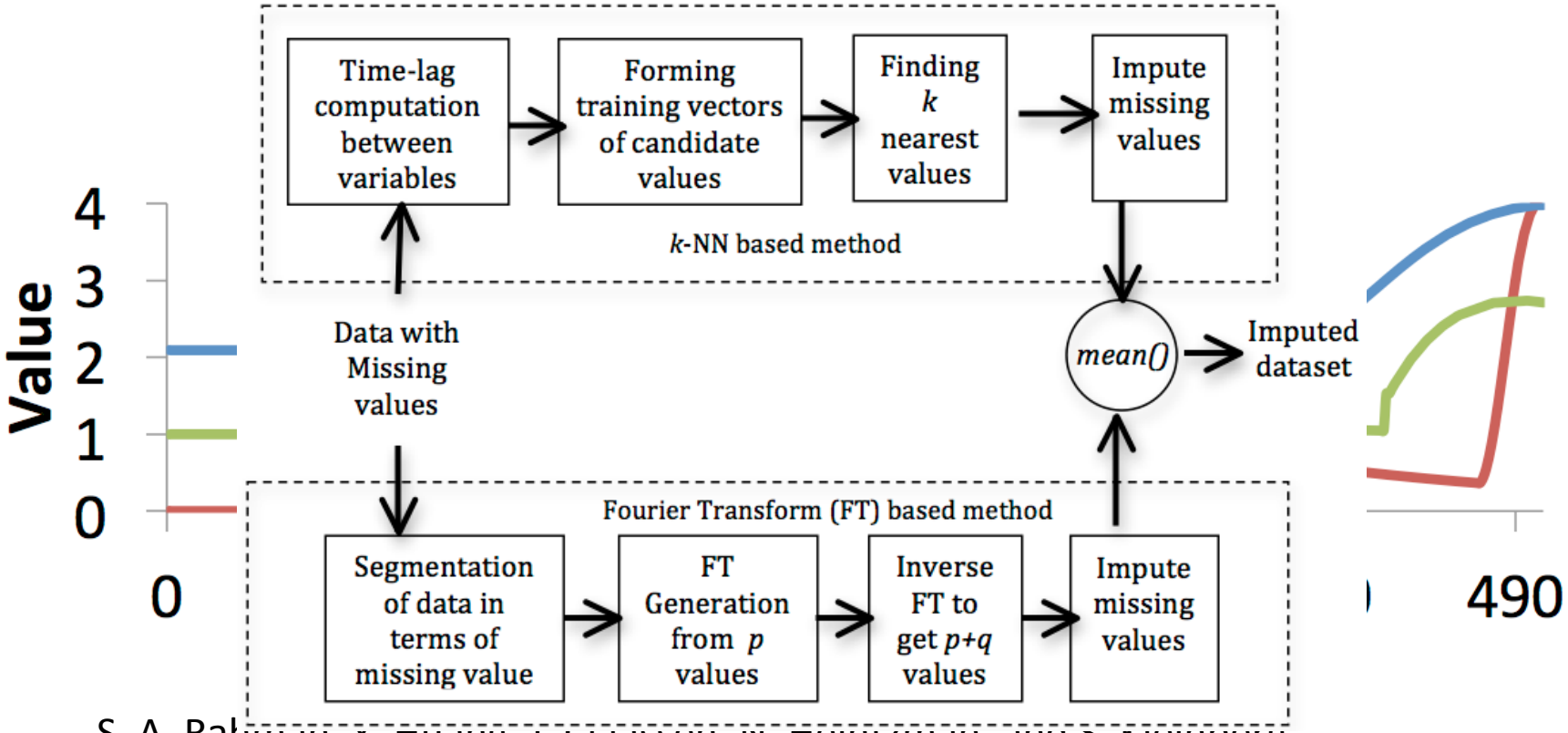
- Device malfunctions
- Device connected to perform a procedure



And…

- All variables may be missing at once (if measured by single device)
  - Can't use imputation methods that assume some present values
- Missing values depend on variable + other variables
  - e.g. BG depends on itself, as well as insulin
- Variables are correlated across time

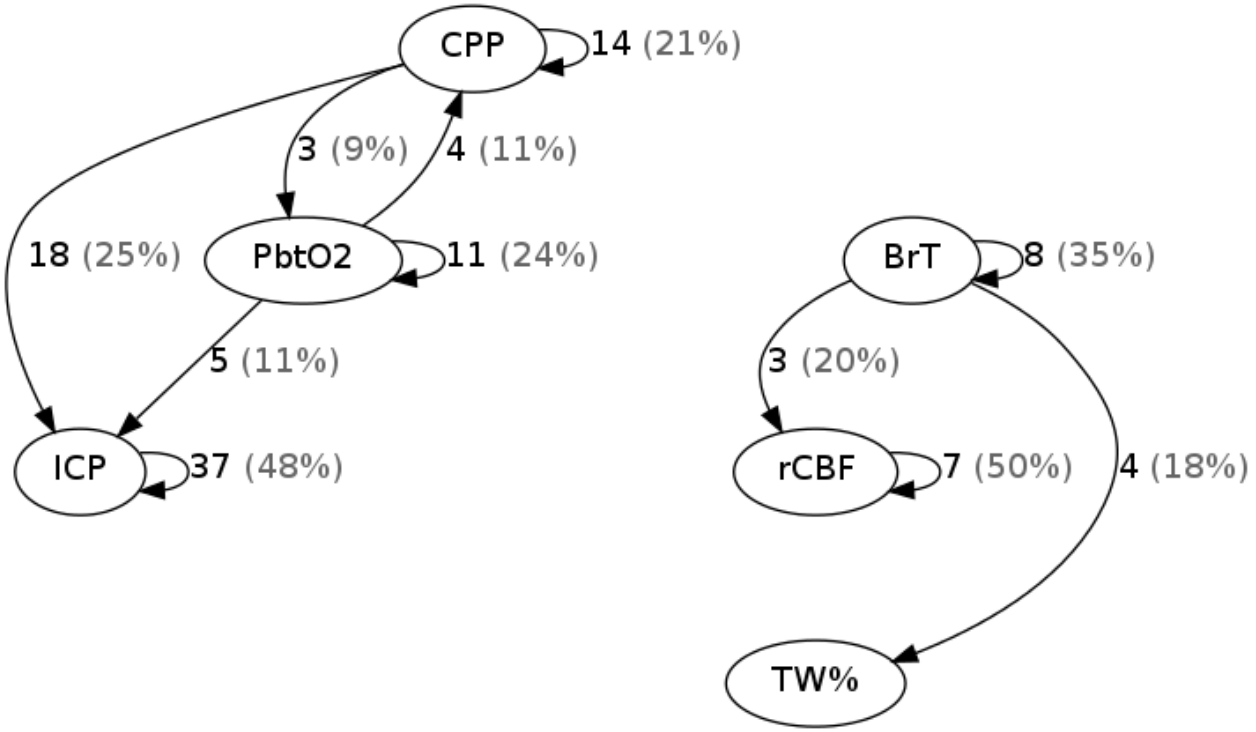
Imputation w/lagged correlations



S. A. Rahman, Y. Huang, J. Claassen, N. Heintzman, and S. Kleinberg. Combining Fourier and Lagged k-Nearest Neighbor Imputation for Biomedical Time Series Data. Journal of Biomedical Informatics (2015)

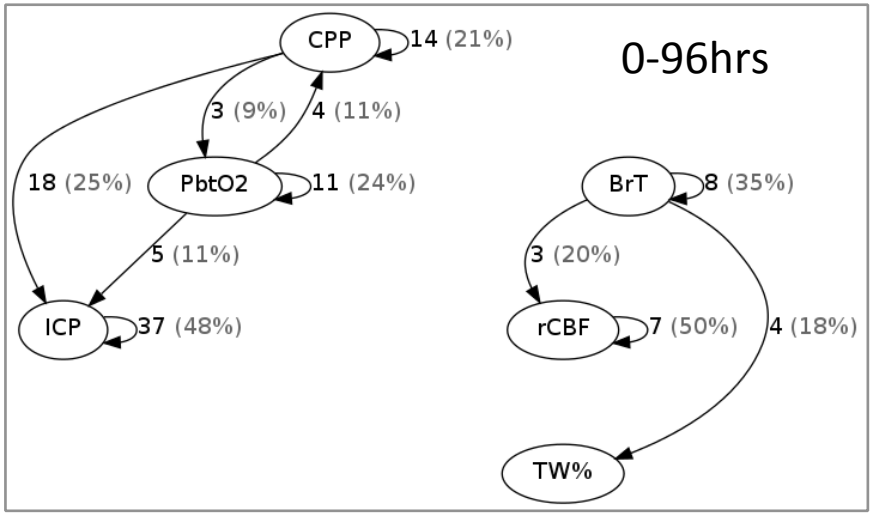
https://github.com/kleinberg-lab/FLK-NN

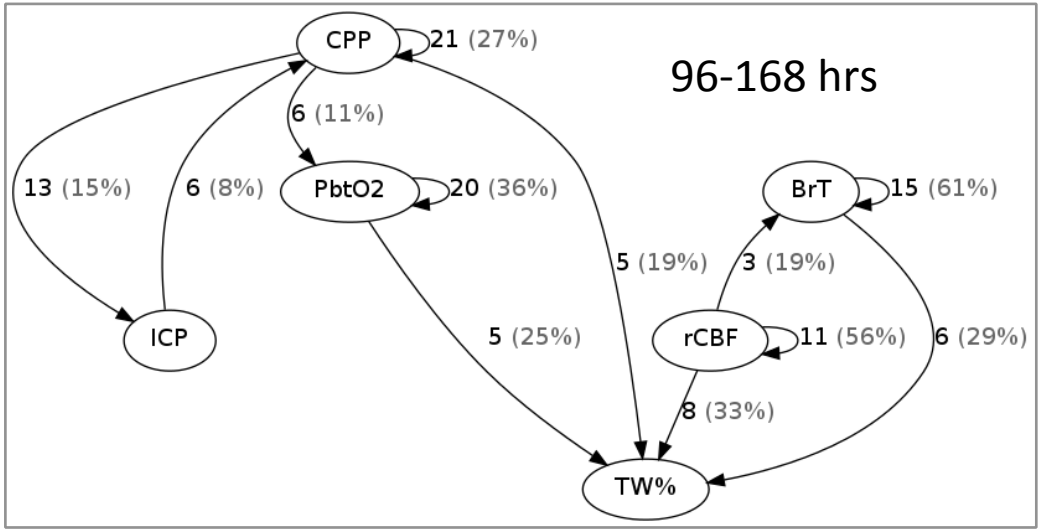
Different data, different physiology

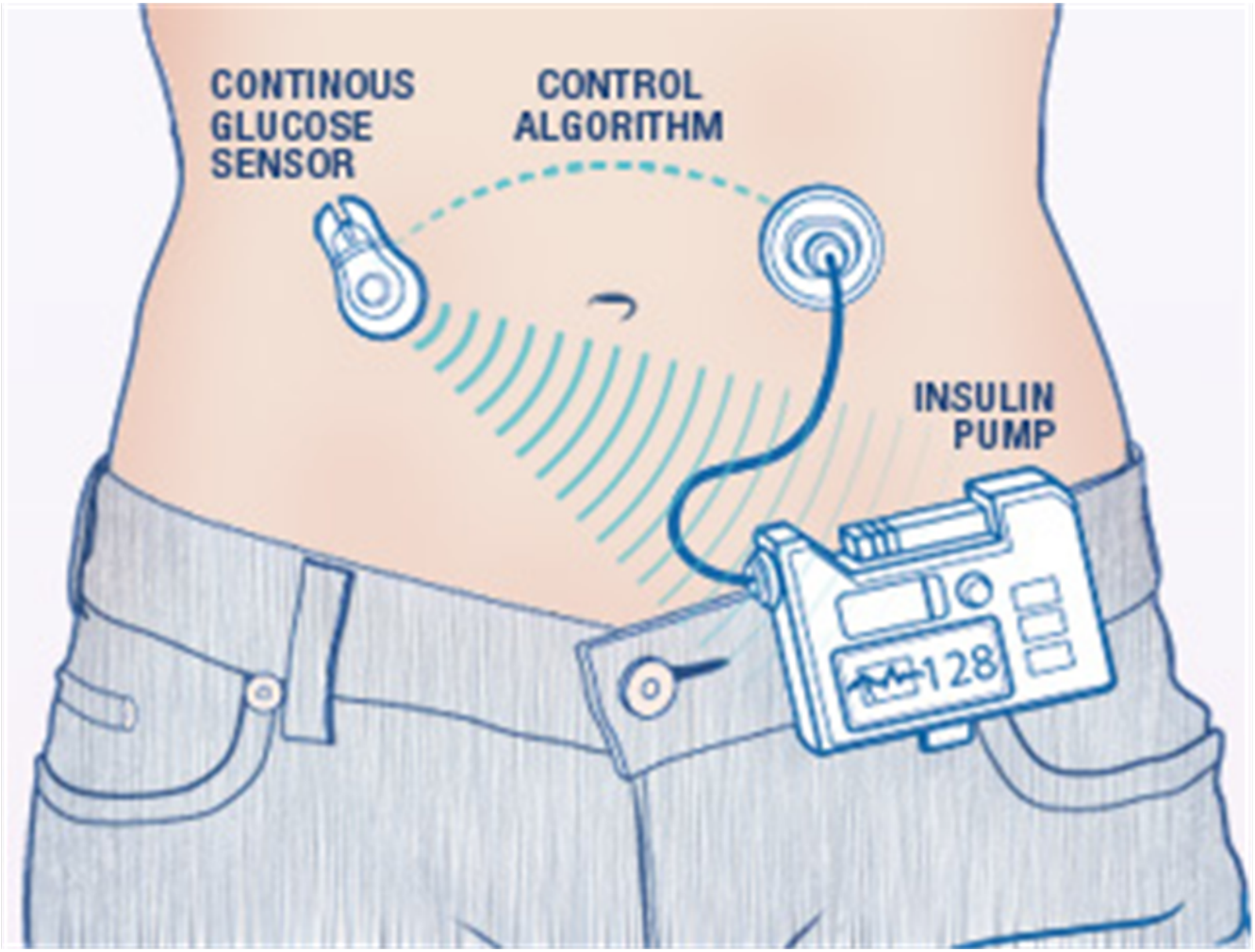


Claassen J, Rahman SA, Huang Y, Frey H, Schmidt M, Albers D, Falo CM, Park S, Agarwal S, Connolly ES, Kleinberg S (2016) Causal structure of brain physiology after brain injury. PLoS ONE.

Regulation changes over time







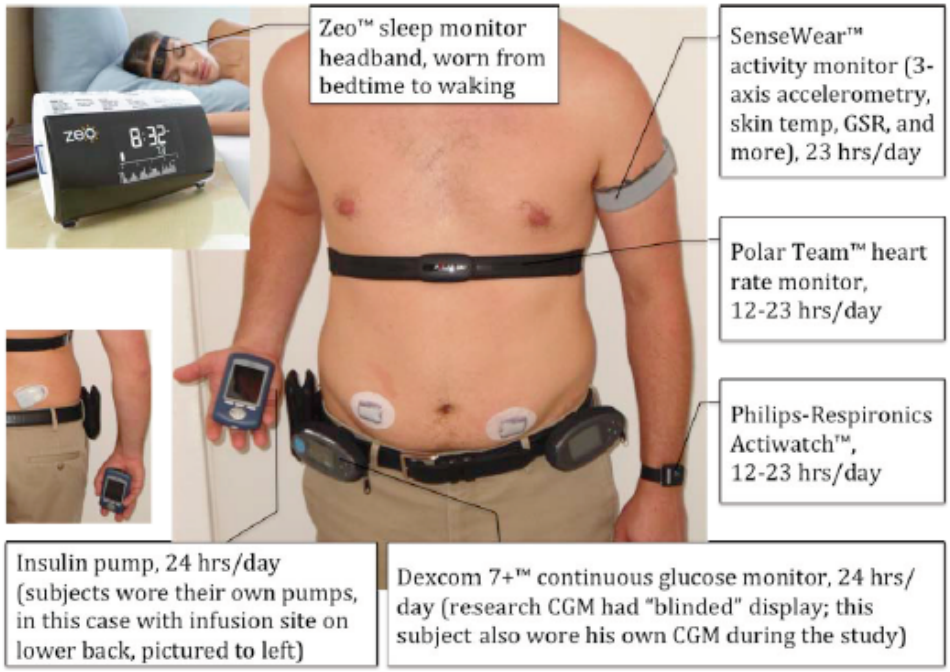
http://discoverysedge.mayo.edu/artificial-pancreas/

Causes of changes in glucose

Cohort: 17 subjects with T1DM

Sensor data (collected for >72 hours)

- Glucose values
- Insulin dosage
- Activity
- Sleep stage
- Heart rate
- Temperature



With N. Heintzman (UCSD) http://dial.ucsd.edu/what-we-do.php

Results

very vigorous exercise leads to hyperglycemia (fdr <.01) in 5-30 minutes

- Found using both HR (anaerobic activity zone) and METs

- Not found with strict discretization
- Supported by literature (Marliss and Vranic, 2002; Riddell and Perkins, 2006)

S. Kleinberg and N. Heintzman. Using uncertain data from body-worn sensors to gain insight into type 1 diabetes. Journal of Biomedical Informatics, 2016.

Why are you here?

Why health informatics?



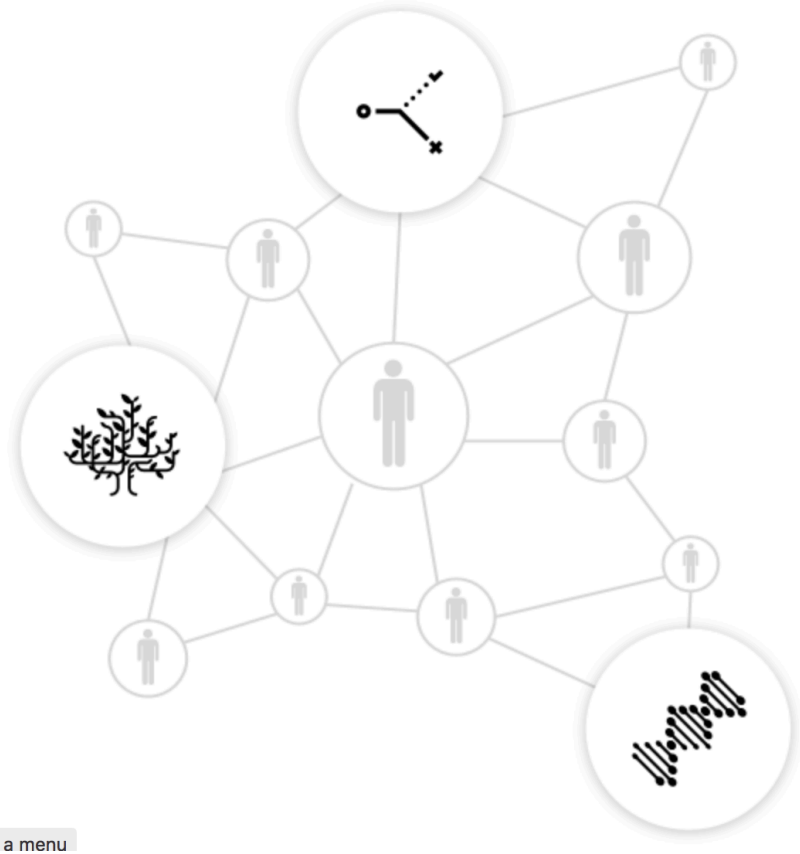
https://www.nih.gov/AllofUs-Research-Program

WHAT ARE THE GOALS?

Engage a group of **1 million or more U.S. research participants** who will share biological samples, genetic data and diet/lifestyle information, all linked to their electronic health records. This data will allow researchers to develop more precise treatments for **many diseases and conditions**.

Pioneer a new model of research that emphasizes **engaged research participants, responsible data sharing and privacy protection.**





Take Control of Your Data

You already shed data through time and space all day long, collected by the corporations that track your spending, location, and use of technology. We at The HUMAN Project believe that the people's data can be better used to serve them, their communities, and society.

What Will We Do?

We will study the lives of 10,000 New York City residents in approximately 4,000 households over the span of decades by collecting measurements across multiple domains and disciplines, and provide this massive, interdisciplinary, and secure dataset to the research community to achieve previously unattainable groundbreaking advancements in medicine, the social sciences, and understanding the true nature of human behavior, while fostering evidenced-based public policies.

Why Now?

a menu

What could we do with this?

- Who’s the user?
- What problem do they have?
- How can CS help?

But what do we need to know first?

- What's the data actually? Is it correct?
- Can we really apply ML/DM methods to it? What are the challenges?
- Can we share data freely? Why not?
- How do we preserve privacy

(and much more)

Syllabus

Prerequisites None. The course is intended for advanced undergraduate and graduate students from computer science and other disciplines.

Text There is no required textbook. Readings are articles that will be provided.

Evaluation Discussion of the readings is an important part of the course and will count towards the final grade. It is not possible to succeed in this course without participating. There will be a final project (and presentation), as well as one presentation for the journal club assignment and discussions of case studies.

Grades will be: 10% homework, 15% participation, 25% midterm exam, 50% final project.

Contact

Samantha Kleinberg
306 Lieb
samantha.kleinberg@stevens.edu
Office hours are Monday 2-2:45pm and by appointment.

Lecture Monday 3-5:30pm

Schedule

Below is the weekly schedule of topics, readings for each session, and deadlines. All journal articles will be available electronically through the library or in Canvas. Readings may change, but in that case an announcement will be made in class.

1/23 Introduction to health informatics. Overview of field, relation to bioinformatics

1/30 Where and why is health data collected? (including meaningful use and PPACA). Including claims data, clinician-generated data, and information exchange.
- P. Wicks, T. E. Vaughan, M. P. Massagli, and J. Heywood. Accelerated clinical discovery using self-reported patient data collected online and a patient-matching algorithm. *Nature biotechnology*, 29(5):411–414, 2011 [pdf]

2/6 What are the data? EMRs, PHRs, and data standards (narrative vs. structured data, ontologies)
- S. Abhyankar, D. Demner-Fushman, F. M. Callaghan, and C. J. McDonald. Combining structured and unstructured data to identify a cohort of icu patients who received dialysis. *Journal of the American Medical Informatics Association*, 1 2014 [pdf]

2/13 Cancelled

2/22 Ethics in biomedical research. HIPAA, IRBs, and de-identification. We will discuss the rules and regulations governing health research and, from a practical standpoint, how to preserve privacy when conducting research
- E. Vayena, R. Brownsword, S. J. Edwards, B. Greshake, J. P. Kahn, N. Ladher, J. Montgomery, D. O'connor, O. O'neill, M. P. Richards, et al. Research led by participants: a new social contract for a new kind of research. *Journal of medical ethics*, 2015 [html]

2/27 Data reuse and evaluation challenges (what is a diagnosis really?)
- S. Kleinberg and N. Elhadad. Lessons learned in replicating data-driven experiments in multiple medical systems and patient populations. In *AMIA Annual Symposium*, 2013 [pdf]
- IRB proposals due

3/6 Midterm exam

3/20 Research with EMR data, Introduction to MIMIC dataset
- F. Doshi-Velez, Y. Ge, and I. Kohane. Comorbidity clusters in autism spectrum disorders: an electronic health record time-series analysis. *Pediatrics*, 133, 2014 [pdf]

3/27 Methods for evaluation. How can we compare systems and determine if a project is successful?
- M. Ghassemi, J. Marshall, N. Singh, D. J. Stone, and L. A. Celi. Leveraging a critical care database: selective serotonin reuptake inhibitor use prior

to icu admission is associated with increased hospital mortality. *CHEST Journal*, 145(4):745–752, 2014 [html]
- Project proposals due

4/3 Pharmacovigilance and drug discovery
- R. W. White, N. P. Tatonetti, N. H. Shah, R. B. Altman, and E. Horvitz. Web-scale pharmacovigilance: listening to signals from the crowd. *Journal of the American Medical Informatics Association*, 2013 [pdf]

4/10 Journal club discussion of recent papers in health informatics

4/17 Decision Support
- P. J. O'Connor, J. M. Sperl-Hillen, W. A. Rush, P. E. Johnson, G. H. Amundson, S. E. Asche, H. L. Ekstrom, and T. P. Gilmer. Impact of electronic health record clinical decision support on diabetes care: a randomized trial. *The Annals of Family Medicine*, 9(1):12–21, 2011 [pdf]

4/24 Public health, epidemiology, and mobile health
- M. Rabbi, M. H. Aung, M. Zhang, and T. Choudhury. Mybehavior: automatic personalized health feedback from user behaviors and preferences using smartphones. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, pages 707–718. ACM, 2015 [pdf]

5/1 Presentations of final projects
- Written project reports due

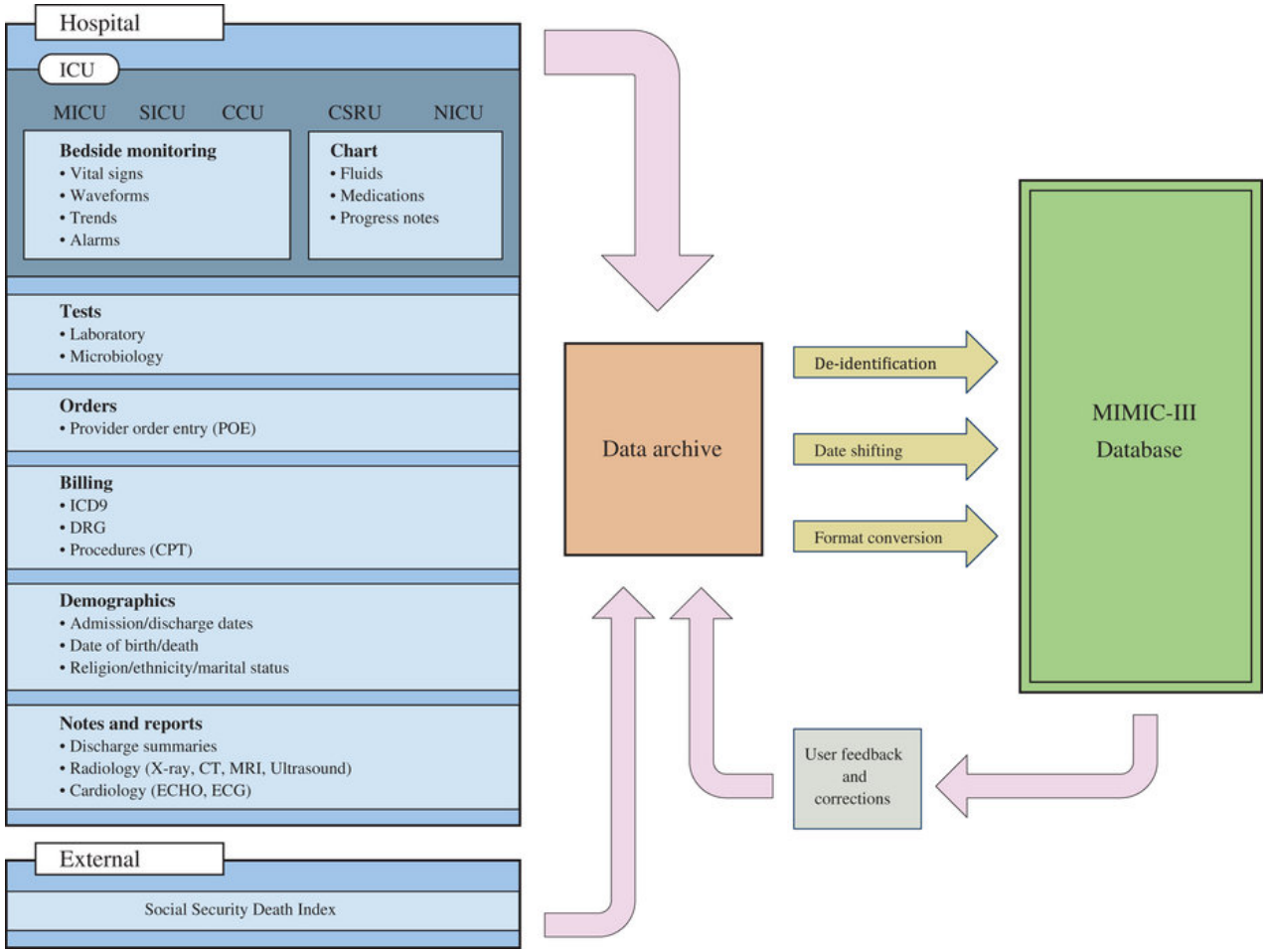
Final projects



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

MIMIC-III, a freely accessible critical care database. Johnson AEW, Pollard TJ, Shen L, Lehman L, Feng M, Ghassemi M, Moody B, Szolovits P, Celi LA, and Mark RG. Scientific Data (2016). DOI: 10.1038/sdata.2016.35.
Available from: http://www.nature.com/articles/sdata201635

https://mimic.physionet.org



Johnson, A. E. W. *et al.* MIMIC-III, a freely accessible critical care database. *Sci. Data* 3:160035 doi: 10.1038/sdata.2016.35 (2016).

Administrativia

- Course website: http://www.skleinberg.org/teaching/HI17/
- Prerequisites: none
- Textbook: **none**, articles
- Topics/readings on syllabus MAY CHANGE (will make announcement in class)
- Workload/grading:

  midterm presentation (25%), final project (50%), participation (15%), homework (10%)

Key policies

1. No late work. There are few deadlines, but if the deadline's 11:59pm, work submitted at 12:01am isn't accepted

   (Why? Try submitting an NIH grant 2 minutes late!)

2. Plagiarism = F

What's plagiarism?

Presenting someone else's work as your own

- Copying an entire paper
- Copying parts of other works, without attribution
  - E.g. quotes without citations
- Changing a few words, but keeping ideas and structure, without acknowledging source

Easy to avoid! Do your own work and acknowledge all sources. Quotes must be in quotes. Don't submit a collage.

1. Quotes belong in quotation marks

- WRONG!
  - Blah blah. Text from other papers. Blah Blah. [Citation]
  - Section 1 [Citation]. Quotes text quotes.

- Right ☺
  - My text “Quote from awesome work.” [citation] my text

3. No copying/close paraphrasing

Don't Let This Be You!

2006: Kaavya Viswanathan, Harvard sophomore, 2-book deal from Little, Brown





Plagiarized!



Sloppy Firsts (2001), page 7: "Bridget is my age and lives across the street. For the first twelve years of my life, these qualifications were all I needed in a best friend. But that was before Bridget's braces came off and her boyfriend Burke got on, before Hope and I met in our seventh grade Honors classes" (McCafferty, quoted in Zhou, "Examples…").

Opal Mehta (2006), page 14: "Priscilla was my age and lived two blocks away. **For the first** fifteen years of my life**, those were the only qualifications I needed in a best friend**. … **But that was before** freshman year, when Priscilla's glasses **came off**, and the first in a long string of boyfriends **got on**" (Viswanathan, quoted in Zhou, "Examples…").

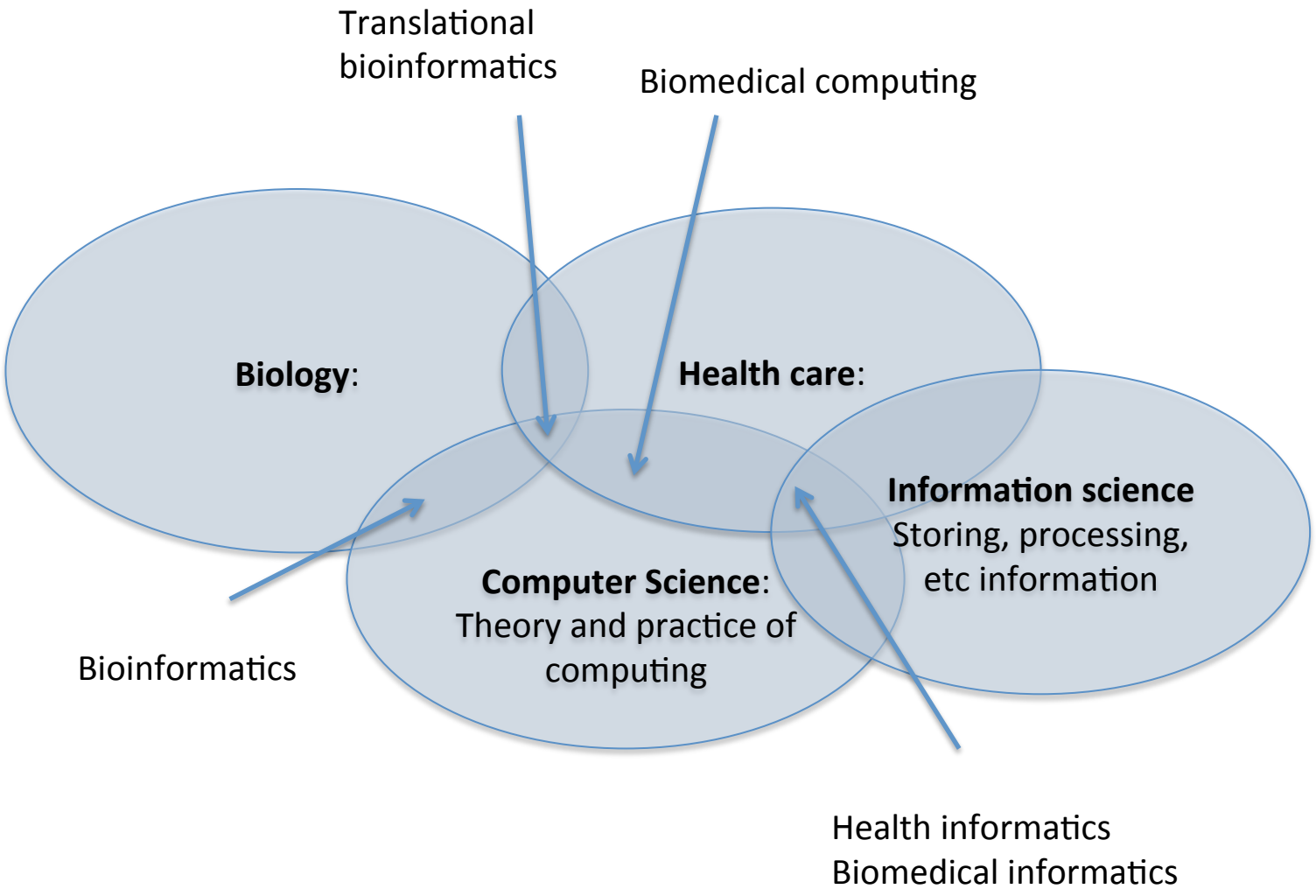
"an act of literary identity theft"
(Steve Ross, qtd. in Zhou, "Publisher…")

http://researchguides.stevens.edu/plagiarism

If you're having trouble…

- Come to office hours! Monday 2-3 in Lieb 306 and by appointment
- Email me

What’s health informatics?

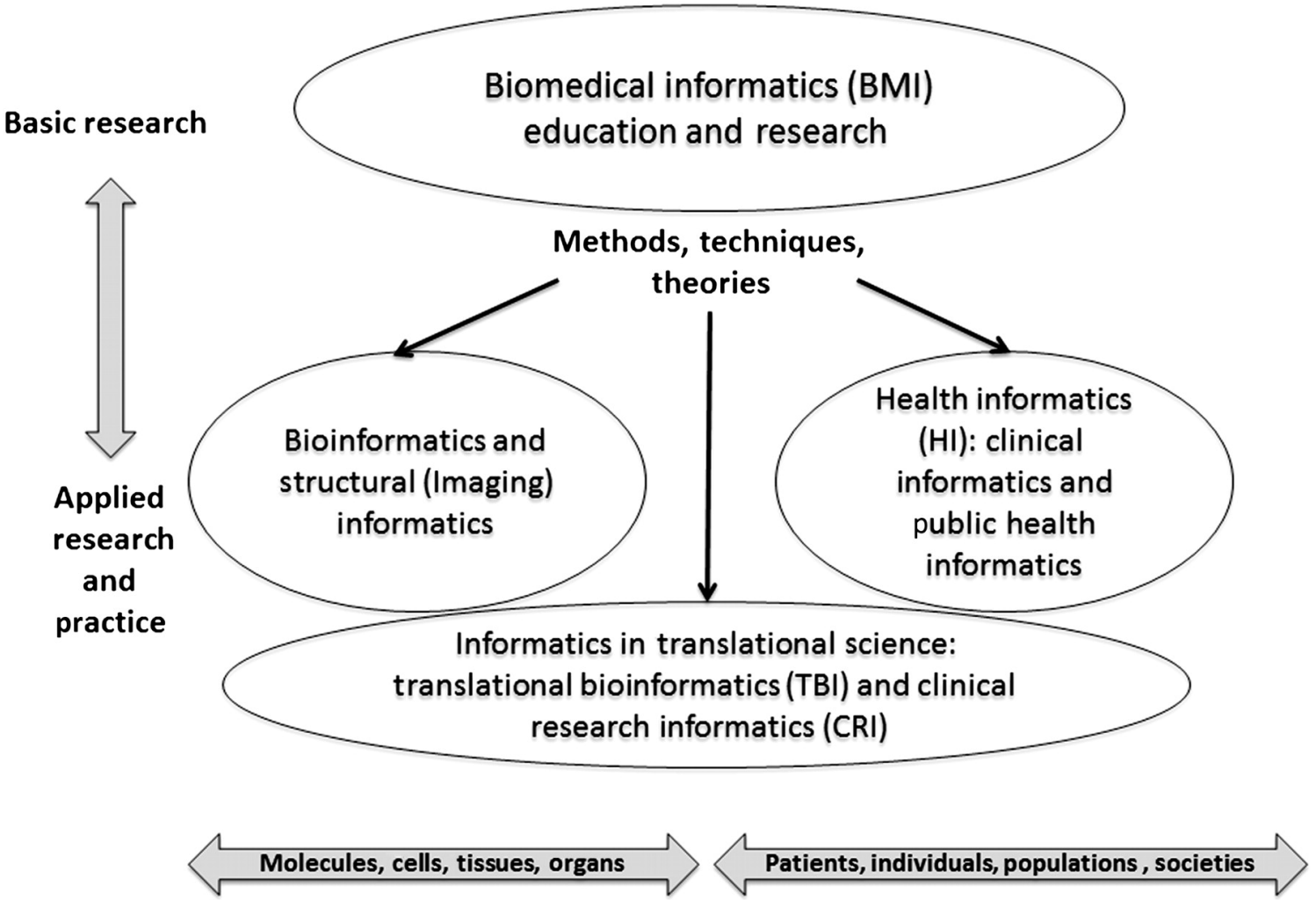

Translational bioinformatics
Biomedical computing
Biology:
Health care:
Information science
Storing, processing, etc information
Computer Science:
Theory and practice of computing
Bioinformatics
Health informatics
Biomedical informatics

Another definition

- **Definition**: Biomedical informatics (BMI) is the interdisciplinary field that studies and pursues the effective uses of biomedical data, information, and knowledge for scientific inquiry, problem solving, and decision making, driven by efforts to improve human health.
- **Scope and breadth of discipline:** BMI investigates and supports reasoning, modeling, simulation, experimentation, and translation across the spectrum from molecules to individuals and to populations, from biological to social systems, bridging basic and clinical research and practice and the healthcare enterprise.
- **Theory and methodology:** BMI develops, studies, and applies theories, methods, and processes for the generation, storage, retrieval, use, management, and sharing of biomedical data, information, and knowledge.
- **Technological approach:** BMI builds on and contributes to computer, telecommunication, and information sciences and technologies, emphasizing their application in biomedicine.
- **Human and social context:** BMI, recognizing that people are the ultimate users of biomedical information, draws upon the social and behavioral sciences to inform the design and evaluation of technical solutions, policies, and the evolution of economic, ethical, social, educational, and organizational systems.

Kulikowski, C.A., Shortliffe, E.H., Currie, L.M., Elkin, P.L., Hunter, L.E., Johnson, T.R., Kalet, I.J., Lenert, L.A., Musen, M.A., Ozbolt, J.G., Smith, J.W., Tarczy-Hornoch, P.Z. & Williamson, J.J., 2012, AMIA Board white paper: definition of biomedical informatics and specification of core competencies for graduate education in the discipline, *Journal of the American Medical Informatics Association*, pp. amiajnl-2012-001053

Biomedical informatics and its areas of application and practice, spanning the range from molecules to populations and society (adapted from Shortliffe and Blois3).



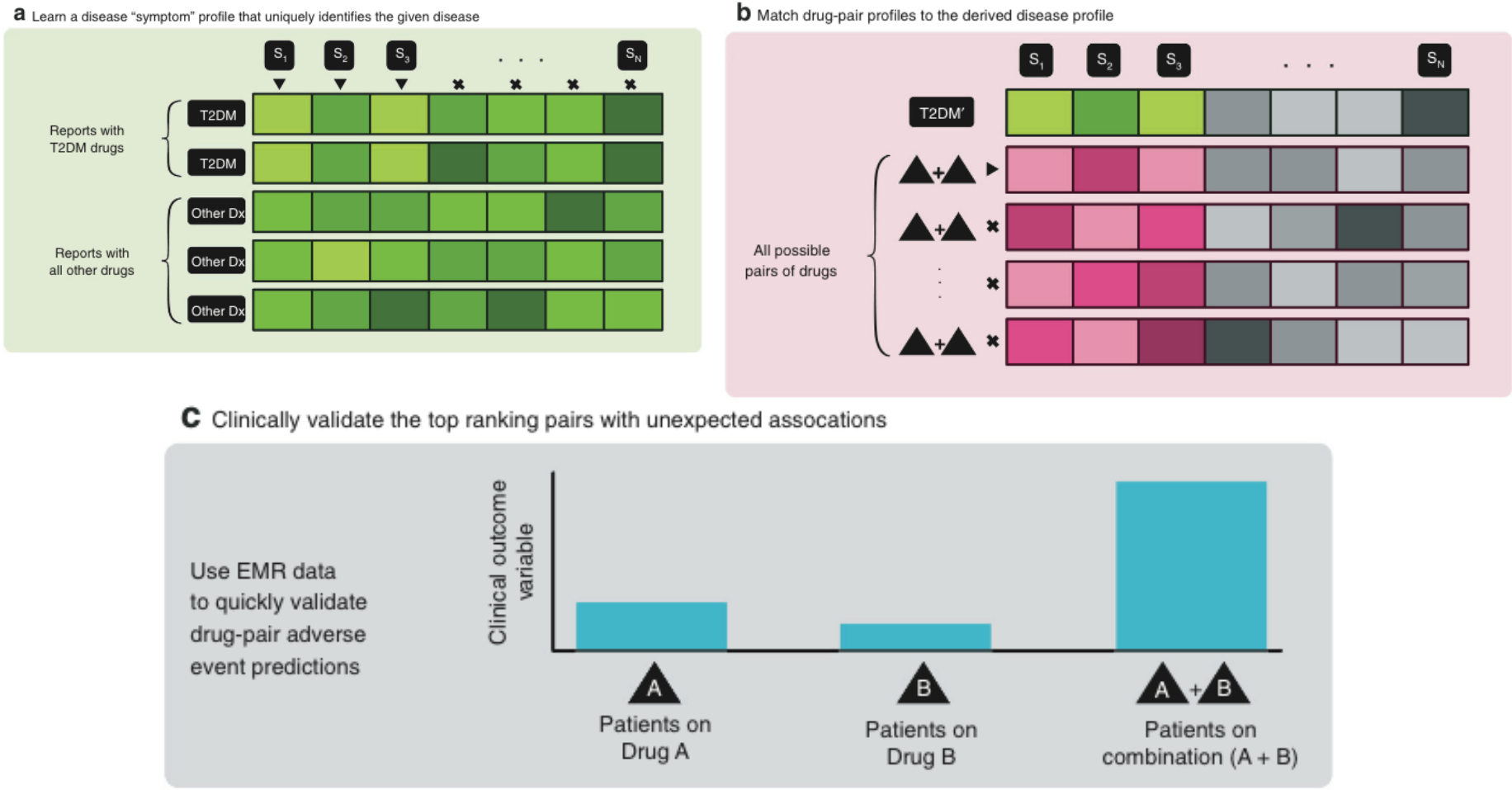
Kulikowski C A et al. J Am Med Inform Assoc doi:10.1136/amiajnl-2012-001053

Copyright © by the American Medical Informatics Association. All rights reserved.

Main subfields

- (Translational) Bioinformatics
- Public health informatics
- Healthcare/Clinical informatics
- Consumer/mHealth

Example: Translational bioinformatics



Tatonetti, N.P., Denny, J.C., Murphy, S.N., Fernald, G.H., Krishnan, G., Castro, V., Yue, P., Tsau, P.S., Kohane, I., Roden, D.M. & Altman, R., 2011, Detecting drug interactions from adverse-event reports: interaction between paroxetine and pravastatin increases blood glucose levels, *Clinical Pharmacology & Therapeutics*, 90(1), pp. 133-42

Example: Predicting cancer stage from online health forum text

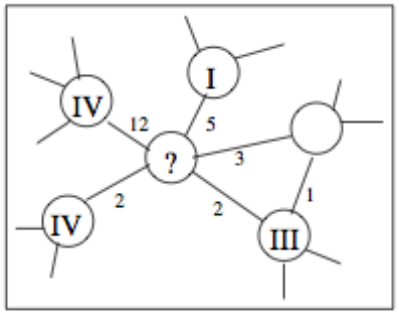


Figure 1: Nodes in the social network of forum member interaction.

Baseline				Text Based			
Stage	Precision	Recall	F	Stage	Precision	Recall	F
I	76.2	26.4	39.3	I	54.9	63.9	59.1
II	79.4	18.7	30.3	II	51.6	55.0	53.2
III	76.6	35.0	48.0	III	52.7	30.3	38.5
IV	76.4	50.7	60.9	IV	82.5	71.2	76.4
Network Based				Combined			
Stage	Precision	Recall	F	Stage	Precision	Recall	F
I	50.4	56.7	53.4	I	57.1	65.4	61.0
II	49.6	49.1	49.3	II	56.6	53.5	55.0
III	65.7	27.7	39.0	III	56.1	48.3	51.9
IV	59.3	83.7	69.4	IV	84.7	81.3	83.0

Table 3: Stage prediction results (Precision, Recall, and F-measure).

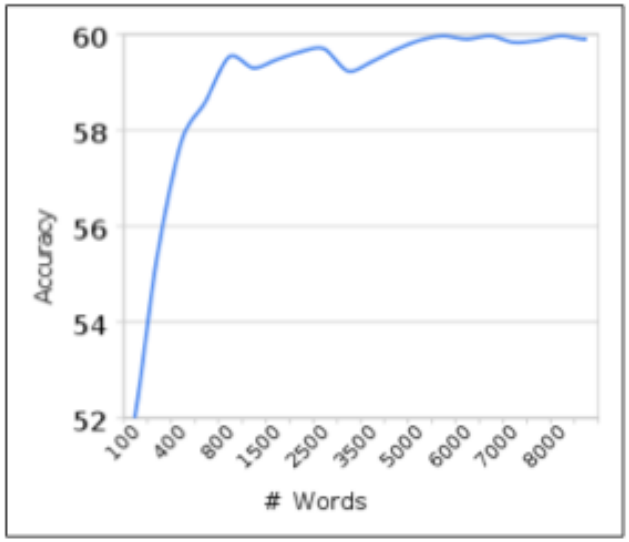


Figure 3: Overall text-based prediction accuracy against post history length.

Mukund Jha and Noemie Elhadad. Cancer stage prediction based on patient online discourse. In Proceedings of the 2010 Workshop on Biomedical Natural Language Processing, pages 64–71, Uppsala, Sweden, July 2010

Example: Clinical informatics

Research and applications

OPEN ACCESS

Reduction in medication errors in hospitals due to adoption of computerized provider order entry systems

David C Radley,[1] Melanie R Wasserman,[2] Lauren EW Olsho,[2] Sarah J Shoemaker,[2] Mark D Spranca,[2] Bethany Bradshaw[3]

[1]Institute for Healthcare Improvement, Cambridge, Massachusetts, USA
[2]US Health Division, Abt Associates Inc, Cambridge, Massachusetts, USA
[3]School of Public Health, Johns Hopkins University, Baltimore, Maryland, USA

Correspondence to
Dr Lauren Olsho, US Health Division, Abt Associates, Inc, 55 Wheeler St, Cambridge, MA 02138, USA;
lauren_olsho@abtassoc.com

Received 2 August 2012
Revised 19 December 2012
Accepted 10 January 2013
Published Online First
21 February 2013

ABSTRACT

Objective Medication errors in hospitals are common, expensive, and sometimes harmful to patients. This study's objective was to derive a nationally representative estimate of medication error reduction in hospitals attributable to electronic prescribing through computerized provider order entry (CPOE) systems.

Materials and methods We conducted a systematic literature review and applied random-effects meta-analytic techniques to derive a summary estimate of the effect of CPOE on medication errors. This pooled estimate was combined with data from the 2006 American Society of Health-System Pharmacists Annual Survey, the 2007 American Hospital Association Annual Survey, and the latter's 2008 Electronic Health Record Adoption Database supplement to estimate the percentage and absolute reduction in medication errors attributable to CPOE.

Results Processing a prescription drug order through a CPOE system decreases the likelihood of error on that order by 48% (95% CI 41% to 55%). Given this effect size, and the degree of CPOE adoption and use in hospitals in 2008, we estimate a 12.5% reduction in medication errors, or ~17.4 million medication errors averted in the USA in 1 year.

Discussion Our findings suggest that CPOE can substantially reduce the frequency of medication errors in inpatient acute-care settings; however, it is unclear whether this translates into reduced harm for patients.

Conclusions Despite CPOE systems' effectiveness at preventing medication errors, adoption and use in US hospitals remain modest. Current policies to increase CPOE adoption and use will likely prevent millions of additional medication errors each year. Further research is needed to better characterize links to patient harm.

which may further reduce errors. There is also some evidence that CPOE may cause errors.[5] CPOE's impact on medication errors and outcomes remains uncertain because of the varied clinical settings, CPOE system origins (commercial vs created in-house), and quality of existing studies.[6]

With its Healthcare Information Technology for Economic and Clinical Health (HITECH) provision, the American Recovery and Reinvestment Act of 2009 authorized US$20 billion in funding to assist in the development of a robust health information technology (health IT) infrastructure to improve healthcare safety and quality. Among the HITECH Act's provisions are incentive payments to outpatient physicians and hospitals to support health IT implementation, including CPOE implementation as a core requirement.[7]

The ultimate goal of CPOE is improved safety, quality, and value of patient care. Medication errors are an important intermediate, measurable outcome in pursuit of that goal. In this investigation, we examine the impact of CPOE on medication error frequency.

OBJECTIVE

The objective of this study was to provide a baseline national estimate of medication errors averted in hospitals due to use of CPOE, using data on CPOE use in 2008, before implementation of the HITECH Act. The baseline estimate and methodology may be useful to track national progress on CPOE adoption, use, and outcomes, and to inform the evolving federal strategy to build an effective health IT infrastructure.

Consumer informatics

TreatYoSelf: Empathy-driven behavioral intervention for marginalized youth living with HIV

Gabriela Marcu[1], Nadia Dowshen[2], Shuvadittya Saha[1], Ressa Reneth Sarreal[3], Nazanin Andalibi[1]

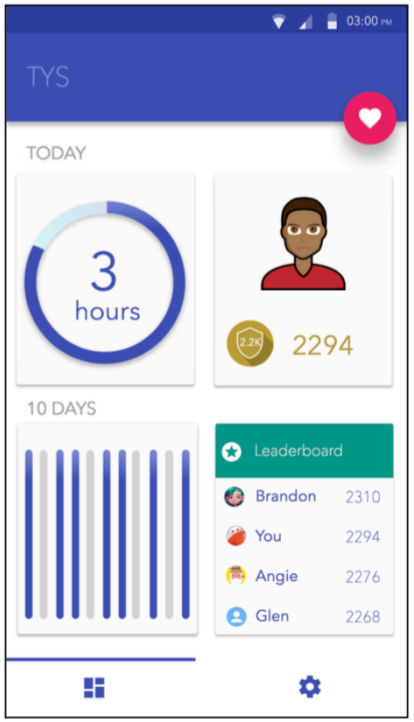
[1] College of Computing and Informatics
Drexel University
Philadelphia, PA
{gmarcu, ss3766, naz}@drexel.edu

[2] Children's Hospital of Philadelphia
Univ. of Pennsylvania School of Medicine
Philadelphia, PA
dowshenn@email.chop.edu

[3] University of Maryland,
Baltimore County
Baltimore, MD
saressa1@umbc.edu

ABSTRACT

Behavioral intervention technologies are well suited to addressing health behavior such as medication adherence, but only if successfully integrated into a user's daily life. Little is known about how to design such technologies to be adoptable, adaptable, useful, and feasible in everyday life. We report on the design process for TreatYoSelf, a smartphone application designed to improve medication adherence among youth living with HIV through reminders and positive reinforcement. Using participatory design, our aim was to understand factors related to adoption and acceptance of behavioral intervention technology as part of daily life. Two challenges of living with HIV led to an empathy-driven approach in our design process: (1) HIV is a stigmatized condition, which (2) disproportionately affects the marginalized populations of young African American men who have sex with men and transgender women. We discuss five empathy-driven design strategies: positive and nonjudgmental tone; minimal, avatar-based gamification; motivational and corny messages; nondisclosure through neutral signifiers; and social support through camaraderie. Our approach enabled us to identify and work through factors, often related to stigma and marginalization, which would lead to rejection of TreatYoSelf use in daily life.



AMIA Themes

- **Biomedical Data Visualization**
- **Clinical Informatics:** findings related to the design, development, and implementation of state-of-the-art clinical systems
- **Clinical Research Informatics:** addressing the critical need for effective information management to address the many challenges facing clinical research
- **Clinical Workflow and Human Factors:** human factors aspects of clinical information system implementation and use that revolves around usability, workflow, and patient safety
- **Consumer Informatics and PHRs:** Personal Health Records (PHRs) and the consumer perspective in the use of health information science designed to improve patient engagement, medical outcomes, and the health care decision-making process
- **Mobile Health:** mHealth, Web 2.0, social media, telehealth/ telemedicine, and related topics
- **Data Interoperability and Information Exchange:** methods that organizations have undertaken to develop and implement various clinical data integration and exchange activities
- **Data Mining, NLP, Information Extraction Retrieval:** application of data mining, natural language processing, information extraction retrieval to all areas of biomedicine
- **Achieving Meaningful Use:** ways to promote the successful and effective development, implementation, and evaluation of Electronic Health Records as the nation works toward "meaningful use" of these systems
- **Global eHealth:** Global eHealth challenges
- **Informatics Education and Workforce Development:** effort to create a trained HIT workforce
- **Informatics in Health Professional Education:** application of information technology in health professional education
- **Interactive Systems:** human-computer interaction (HCI) research, compelling designs, or innovative interactive technologies
- **Policy and Ethical Issues:** unprecedented national HIT activity and ethical considerations posed as more practitioners and the public interface with these technologies.
- **Public Health Informatics and Biosurveillance:** disease detection, communications, workforce development, standards and interoperability, and best practices to combine the domains of health information science and technology with the practice and science of public health
- **Imaging Informatics:** intersection of imaging science, biomedical engineering and biomedical informatics,
- **Simulation and Modeling:** use of various computer-based simulation and modeling methodologies and tools as they can be applied within the field of biomedical informatics
- **Terminology and Standards Ontologies:** complex issues surrounding standard syntax, semantics, and pragmatics of design, development and use of various application-specific and general purpose clinical terminologies and ontologies
- **Translational Bioinformatics and Biomedicine:** opportunities in biomedical informatics that arise from the storage, retrieval, analysis, and dissemination of molecular and genomic information in a clinical setting context

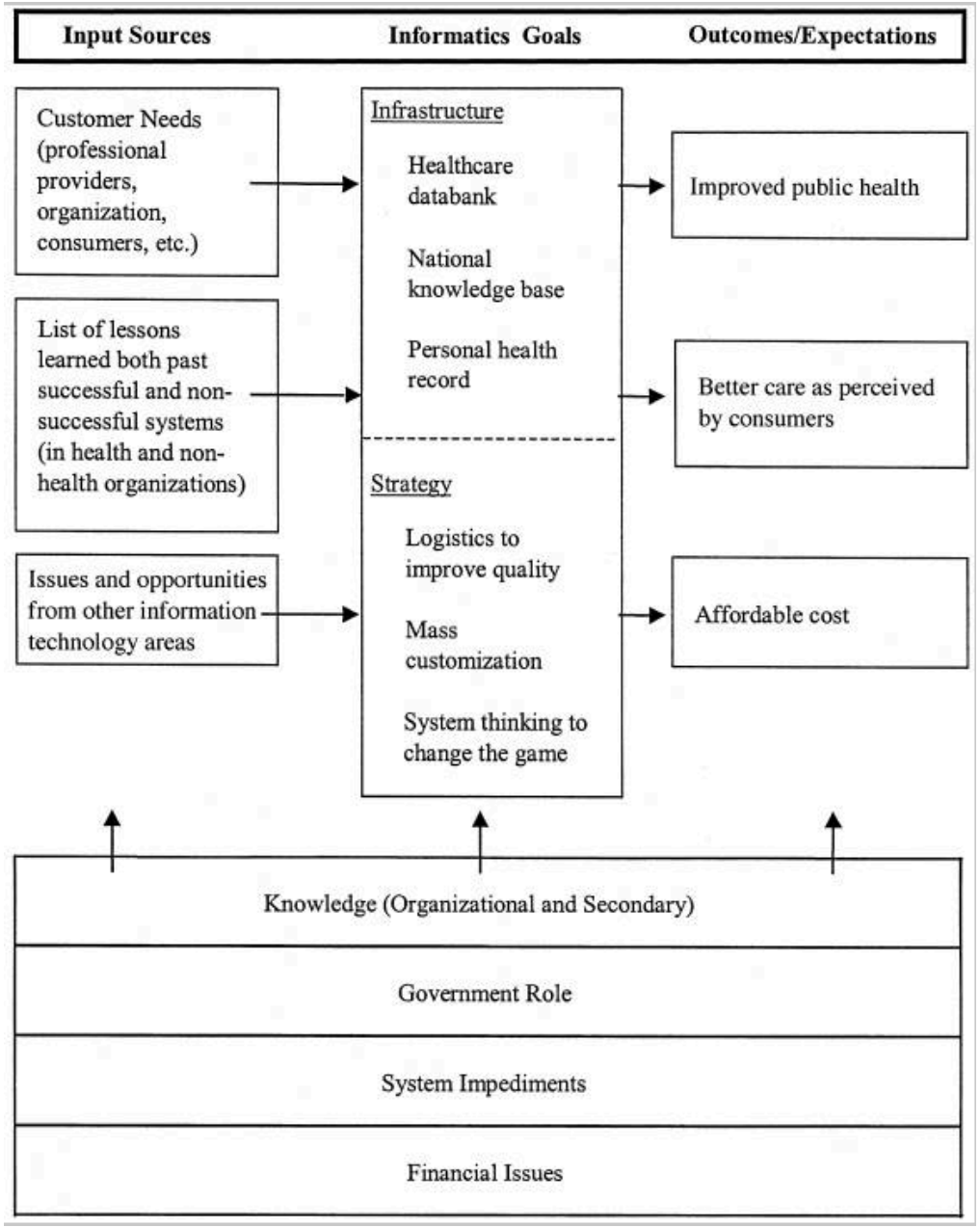
http://www.amia.org/amia2013/themes

Goals

Conceptual Value/Mission Model for Academic Health Centers

Value: Quality	Mission:		
	Patient Care	**Education**	**Research**
Right Thing (*Vision*)	■ Carriage trade	■ Specialists	■ Advancing and communicating knowledge
	■ Individualization	■ Family Practice Physicians	
	■ Mass customization	■ Academic Physicians	■ Outcome research
	■ Population-based medicine	■ Allied Health Professionals	
	■ Regional health model		
Right Way (*Which, How*)	■ Traditional medicine	■ Lecture	■ Laboratory-based research
	■ Complementary medicine	■ Problem-based learning	■ Department/discipline
	■ Evidence-based medicine	■ Small group	■ Interdisciplinary institutes
	■ Standards of care	■ Community-based learning	■ Academic health center
	■ Practice guidelines	■ Apprenticeships	
	■ Protocols		
	■ Learning organization		
	■ Person empowerment		
	■ Shared responsibility		
Right Time (*When*)	■ Acute care on demand	■ Undergraduate medical education	■ Undergraduate education
	■ Preventive medicine		■ Graduate education
	■ Public health education	■ Graduate medical education	
		■ AA/BA education	
		■ Just-in-time learning	
		■ Just-in-time training	
Right Person (*Who*)	■ Physician	■ Physicians	■ Faculty
	■ Integrated staff	■ Other faculty	■ Interdisciplinary team
	■ Skill mix		
	■ Patient		
	■ Consumer/public		

Stead, W.W. & Lorenzi, N.M., 1999, Health Informatics Linking Investment to Value, *Journal of the American Medical Informatics Association*, 6(5), pp. 341-8.



Stead, W.W. & Lorenzi, N.M., 1999, Health Informatics Linking Investment to Value, *Journal of the American Medical Informatics Association*, 6(5), pp. 341-8.

An Envisioned Cycle That Ties Patient Care with Knowledge Creation and Dissemination



Providers Caring for Patients

Electronic Health Records

Regional and National Public Health and Disease Registries

Biomedical and Clinical Research

Standards for Prevention and Treatment

Creation of Protocols, Guidelines, and Educational Materials

Information, Decision-Support, and Order-Entry Systems

A "Learning Healthcare System"

Slide by AMIA

Health IT

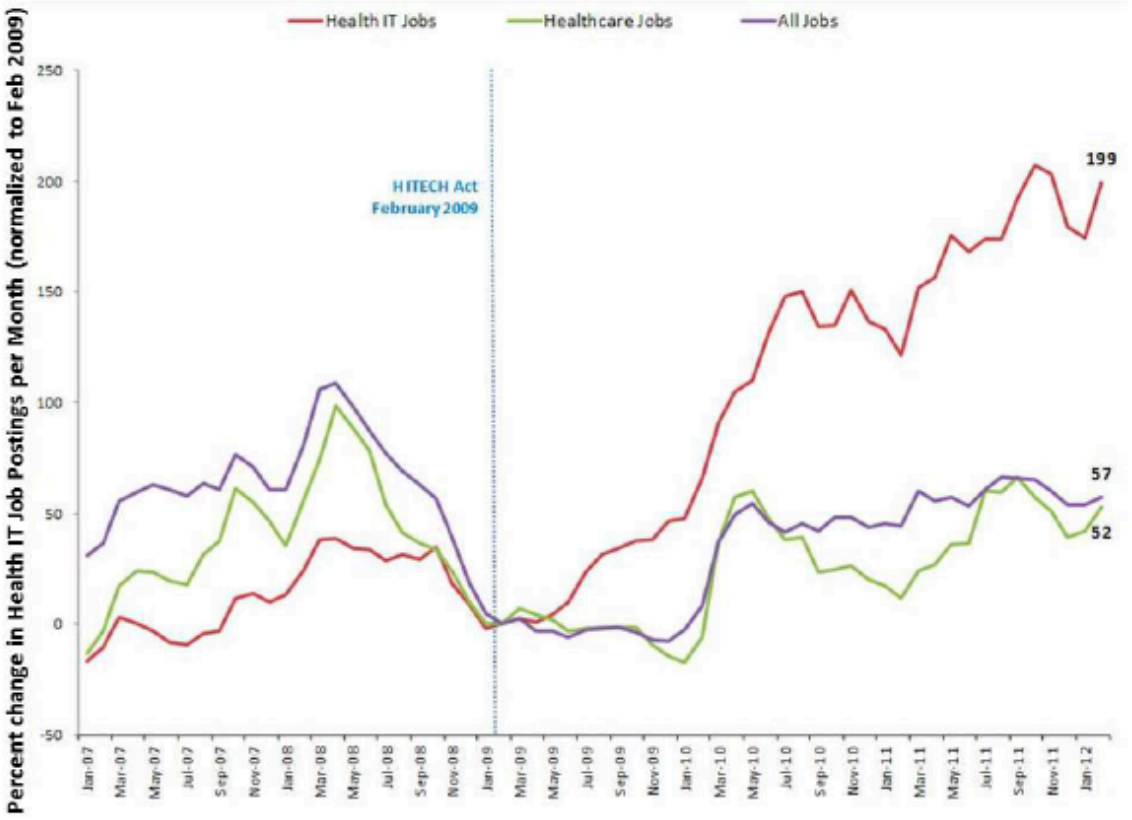
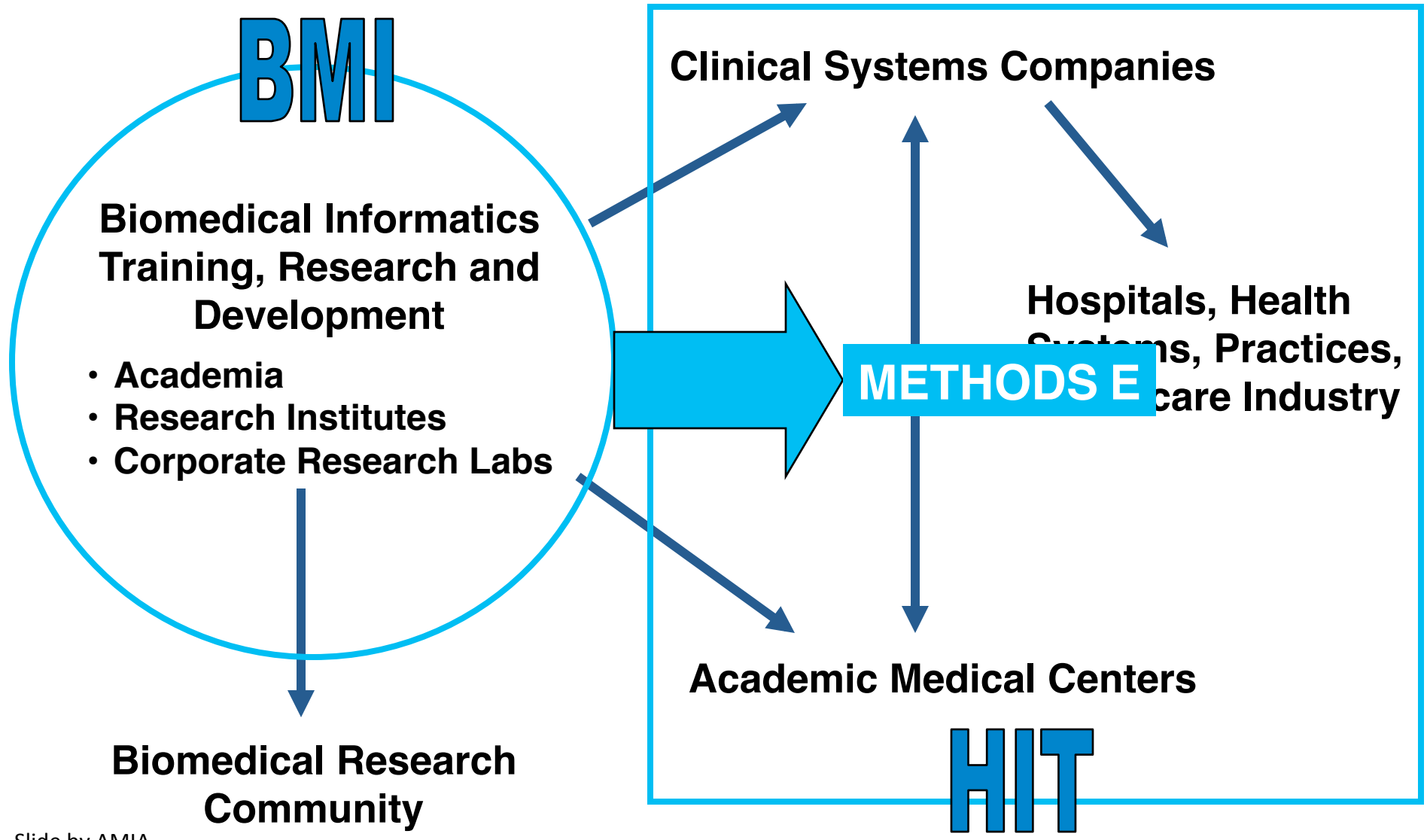


Figure 1.10 Percent change in online health IT job postings per month, relative to healthcare jobs and all jobs: normalized to February 2009 when ARRA passed. Source: ONC analysis of data from O'Reilly Job Data Mart, ONC Data Brief, No. 2, May 2012 [http://www.healthit.gov/sites/default/files/pdf/0512_ONCDataBrief2_JobPostings.pdf (Accessed 4/10/13)]

Shortliffe, E.H. & Cimino, J.J., 2013, *Biomedical Informatics: Computer Applications in Health Care and Biomedicine,* Springer Verla

BMI and HIT



Slide by AMIA

Personalized medicine

Use individual level characteristics and information to tailor treatment

- Choosing between treatments vs. creating individual treatment

Personalized medicine + informatics

- Using -omics in clinical care
- Decision support
- Find similar patients – treatments, outcomes

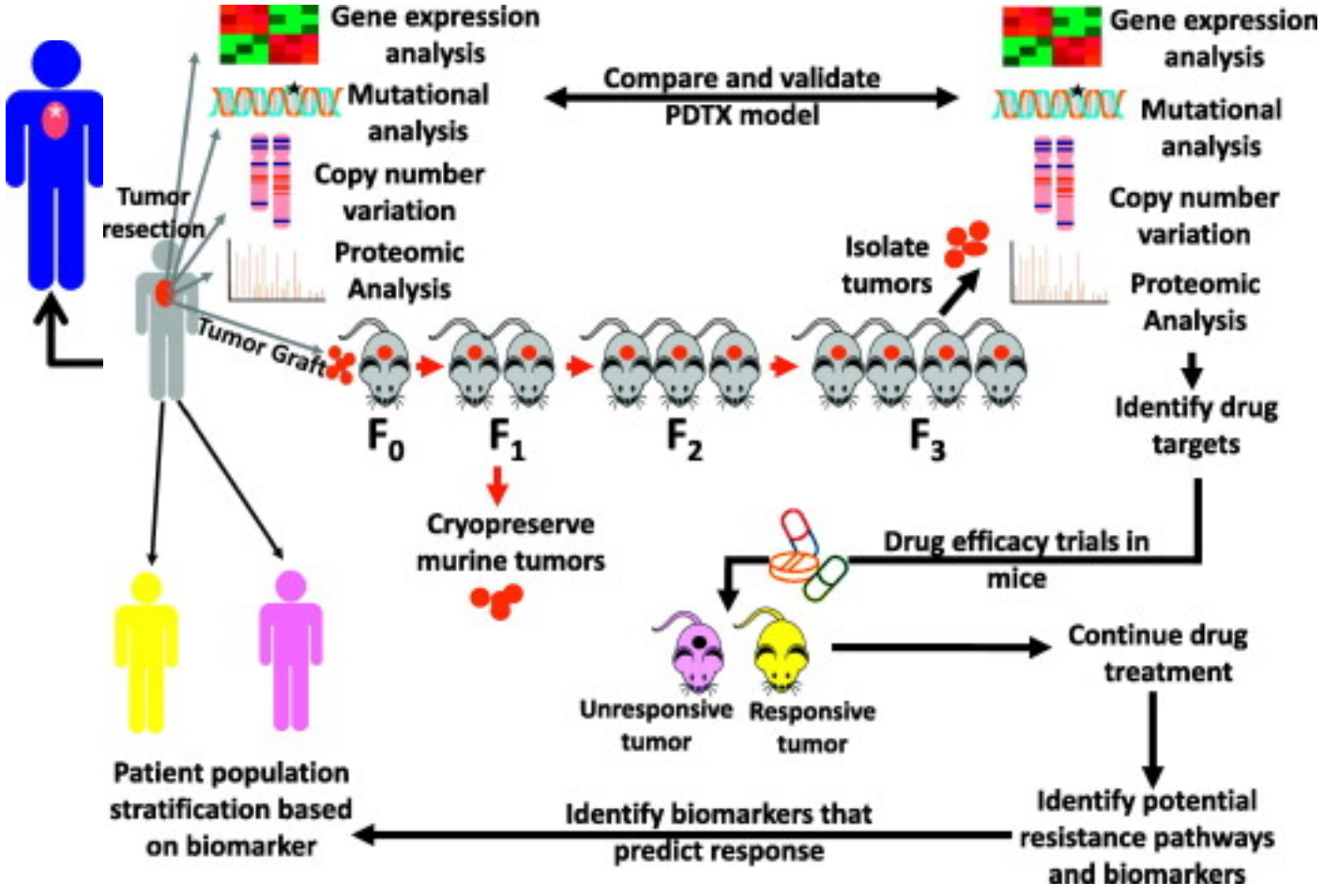
Mini-review

One mouse, one patient paradigm: New avatars of personalized cancer therapy

Prerna Malaney[a], Santo V. Nicosia[a], Vrushank Davé[a, b],

[a] Morsani College of Medicine, Department of Pathology and Cell Biology, Tampa, FL 33612, USA

[b] Department of Molecular Oncology, H. Lee Moffitt Cancer Center and Research Institute, Tampa, FL 33612, USA



Chronic disease

- Diabetes
- Obesity
- Asthma
- Epilepsy

…

Articles Register Sign in

glu

Glu is an active and diverse type 1 diabetes online community designed to accelerate research and amplify the collective voice of those living with T1D. **Register Now.**



Support:
Find and connect with others touched by T1D.

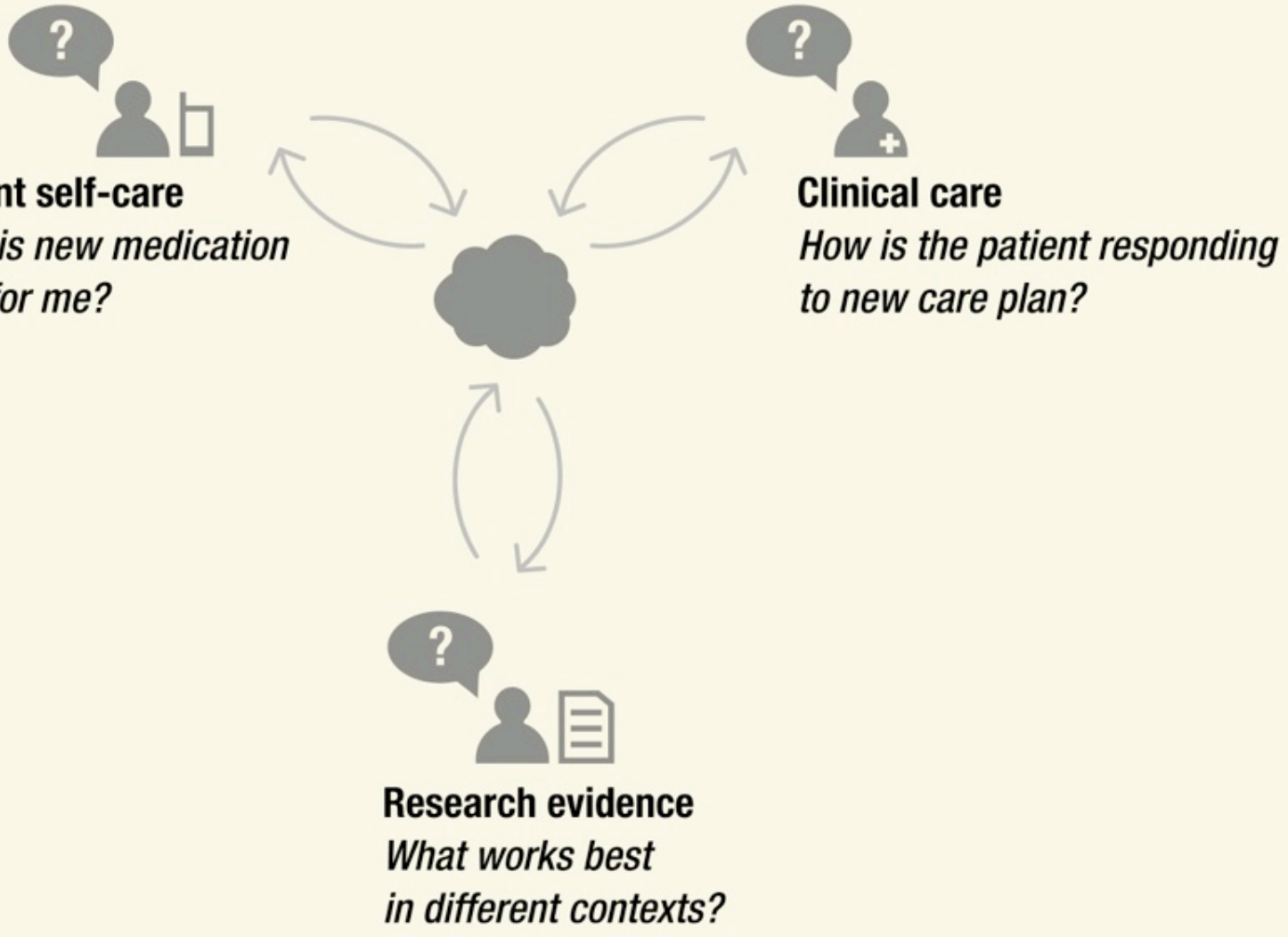


Empower:
Get involved as a citizen scientist to help accelerate research.

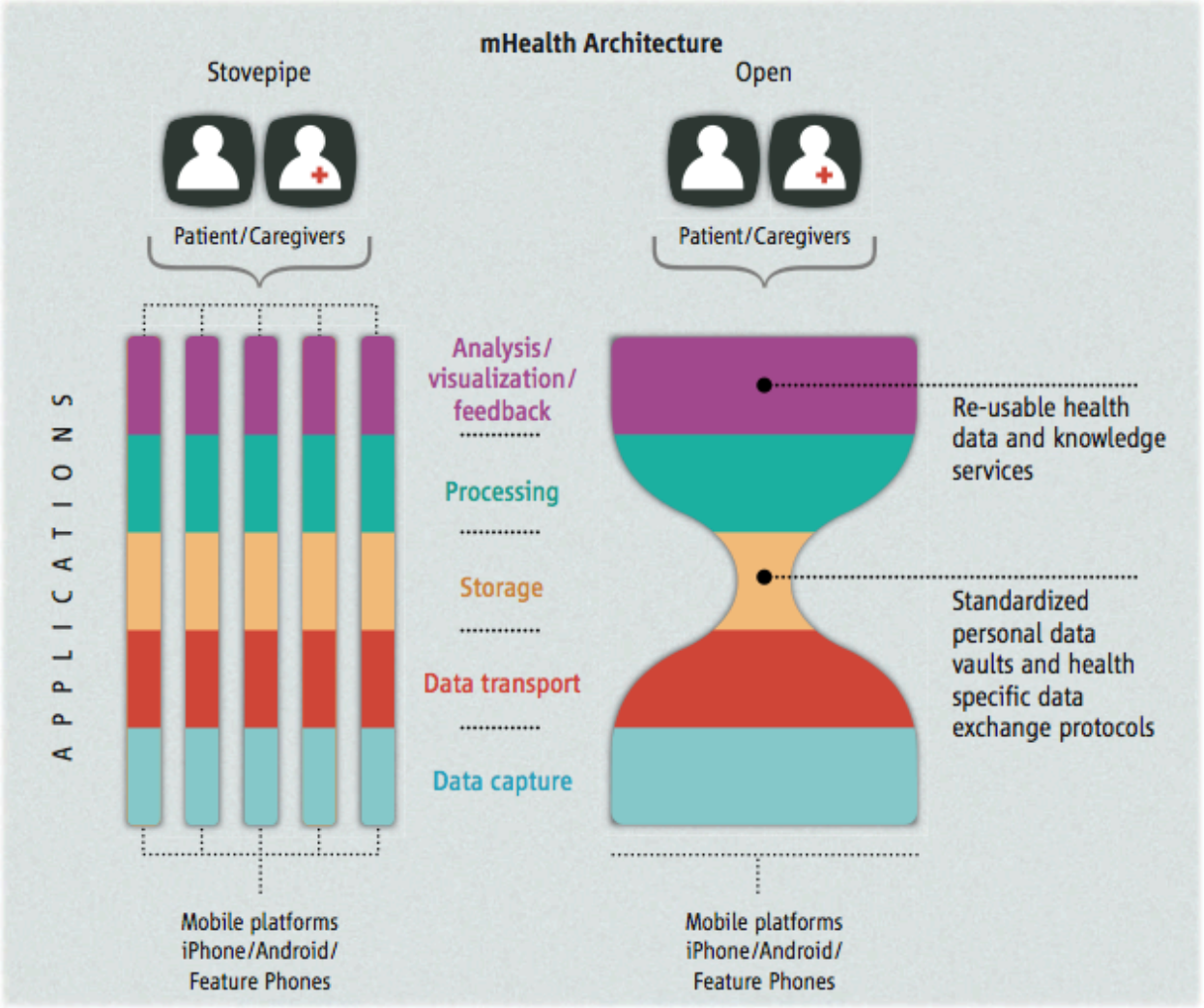


Educate:
Learn from discussions, articles, research, and from each other.

Essential data driven feedback loops



http://mobilizelabs.org/why-mhealth



mHealth architecture: Stovepipe versus Open. The narrow waist of the open hourglass will include at least health-specific syntactic and semantic data standards; patient identity standards; core data processing functions such as feature extraction and analytics; and data stores that allow for selective, patient-controlled sharing. Standards should be common with broader health IT standards whenever possible.

Estrin, D. & Sim, I., 2010, Open mHealth architecture: an engine for health care innovation, *Science(Washington)*, 330(6005), pp. 759-60

Challenges/open problems

- Data
- Replication/validation
- Privacy/sharing
- Translation

For next week

- Be sure to read Wicks et al. paper in syllabus!