Summarizing the Patient Record & Modeling Diseases from EHR Observations

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RESEARCH REPORT

RAND HEALTH

Factors Affecting Physician Professional Satisfaction and Their Implications for Patient Care, Health Systems, and Health Policy

AMA AMERICAN MEDICAL ASSOCIATION

CHAPTER SEVEN

HEALTH CARE

Doctors, hospitals rethinking electronic medical records mandated by 2009 law

BY RICHARD POLLOCK | OCTOBER 10, 2014 | 5:00 AM

(iStock image)

A revolt is brewing among doctors and hospital administrators over electronic medical records systems mandated by one of President Obama's early health care reforms.

The American Medical Association called for a "design overhaul" of the entire electronic health records system in September because, said AMA president-elect Steven Stack, electronic records "fail to support efficient and effective clinical work."

That has "resulted in physicians feeling increasingly demoralized by technology that interferes with their ability to provide first-rate medical care to their patients," Stack said.

http://www.washingtonexaminer.com/doctors-hospitals-rethink-electronic-medical-records-mandated-by-2009-law/article/2554622

Why are doctors frustr

Electronic Health Records - Expensive, Disruptive And Here To Stay

Why electronic medical records are a disaster for some docs

Why

Electronic health records: A 'clunky' transition

Doctors Say Electronic Records Waste Time

cords mess

Why EMR is a dirty word to many doctors

Nurses growing more dissatisfied with EHR systems

AMA pleads for more user-friendly EHRs

http://www.informationweek.com/healthcare/electronic-health-records/why-doctors-hate-ehr-software/d/d-id/1112001?
http://www.kevinmd.com/blog/2012/02/emr-dirty-word-doctors.html
http://www.washingtonpost.com/opinions/americas-electronic-medical-records-mess/2013/09/27/651a81f0-2716-11e3-b75d-5b7f66349852_story.html
http://www.reportingonhealth.org/2014/08/14/why-some-docs-say-electronic-medical-records-are-disaster
http://www.forbes.com/sites/nicolefisher/2014/03/18/electronic-health-records-expensive-disruptive-and-here-to-stay/
http://www.usnews.com/news/articles/2014/09/08/doctors-complain-of-time-wasted-on-electronic-health-records
http://www.politico.com/story/2014/06/health-care-electronic-records-107881.html
http://healthcaretraveler.modernmedicine.com/healthcare-traveler/news/nurses-growing-more-dissatisfied-ehr-systems
http://www.modernhealthcare.com/article/20140916/NEWS/309169936?utm_name=top
http://medcitynews.com/2013/11/doctors-frustrated-using-ehr/

Today we'll be talking about

- What's the story of the patient I am taking care of? What is my patient at risk for?

- Information overload
- (Disease Progression Prediction)
- Summarization of patient record
- Modeling diseases from EHR observations

Information overload

- Present at all levels of care
  - Primary / inpatient / emergency care
  - Health information exchange
- EHR data is cognitively taxing to navigate
  - Lots of it
  - Heterogeneous data
  - Primarily organized chronologically

- McDonald (1976) Protocol-based computer reminders, the quality of care and the non-perfectability of man. N Engl J Med.
- Christensen & Grimsmo (2008) Instant availability of patient records, but diminished availability of patient information: a multi-method study of GP's use of electronic patient records. BMC Med Inform Decis Mak.
- Chase et al (2009). Voice capture of medical residents' clinical information needs during an inpatient rotation. J Am Med Inform Assoc.
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- Adler-Milstein et al (2011) A survey of health information exchange organizations in the United States: implications for meaningful use. Ann of Intern Med.
- Stead & Lin (2009) Computational technology for effective health care: immediate steps and strategic directions. National Research Council of the National Academies.
- Singh et al (2013) Information overload and missed test results in electronic health record-based settings. JAMA Intern Med.

What's my patient at risk for?

- Disease progression prediction
  - Chronic kidney disease (CKD)
  - Difficult for clinicians, because of uncertainty, but also information overload

- State of the art for risk prediction models for CKD
  - Varying model type (Logistic, Cox)
  - Varying features (demographics, eGFR, diagnoses, laboratory tests)
  - Varying outcomes (creatinine, eGFR, complications, kidney failure)

Our goal

- Use **longitudinal**, heterogeneous data sources to predict risk of a near-term CKD outcome that should be sensitive to short-term medical decisions.
- In contrast to previous studies, we:
  - Use EHR data
  - Use longitudinal data (up to 20 years back)
  - Use heterogeneous data (demographics, labs, notes)
  - Use stage III CKD as a trigger for prediction and stage IV as the outcome.

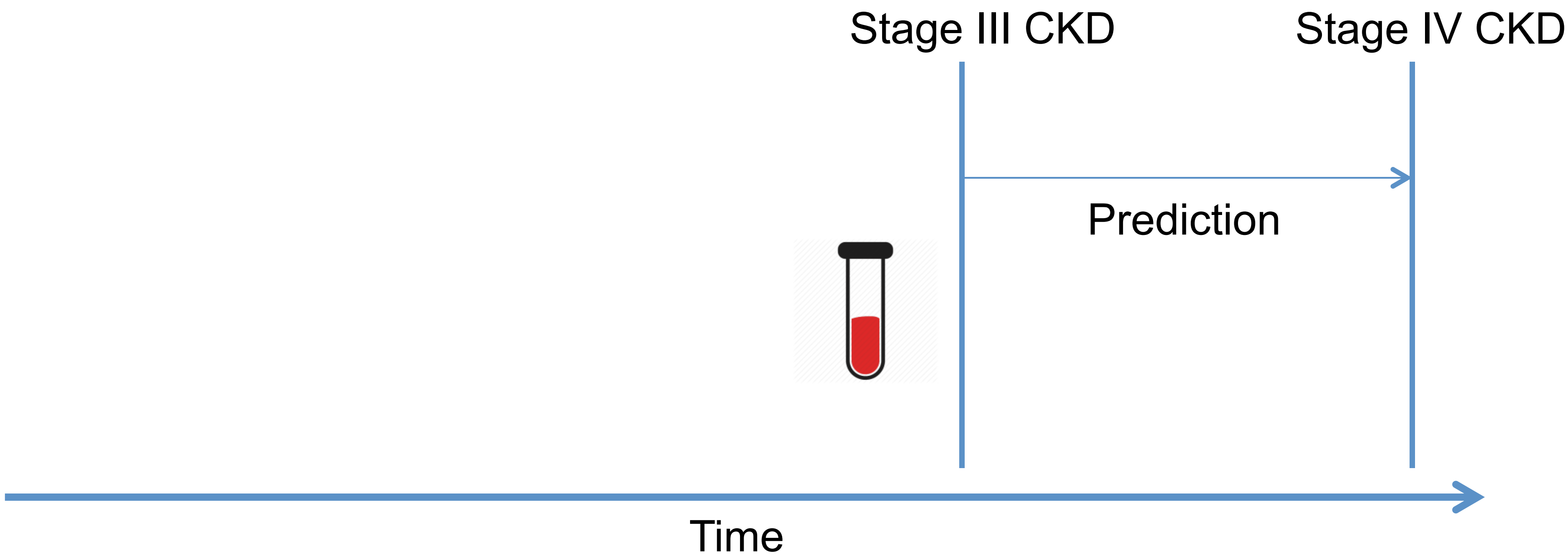
Perotte et al (2015) Risk Prediction for Chronic Kidney Disease Progression Using Heterogeneous Electronic Health Record Data and Time Series Analysis. J Am Med Inform Assoc.

Data + Models

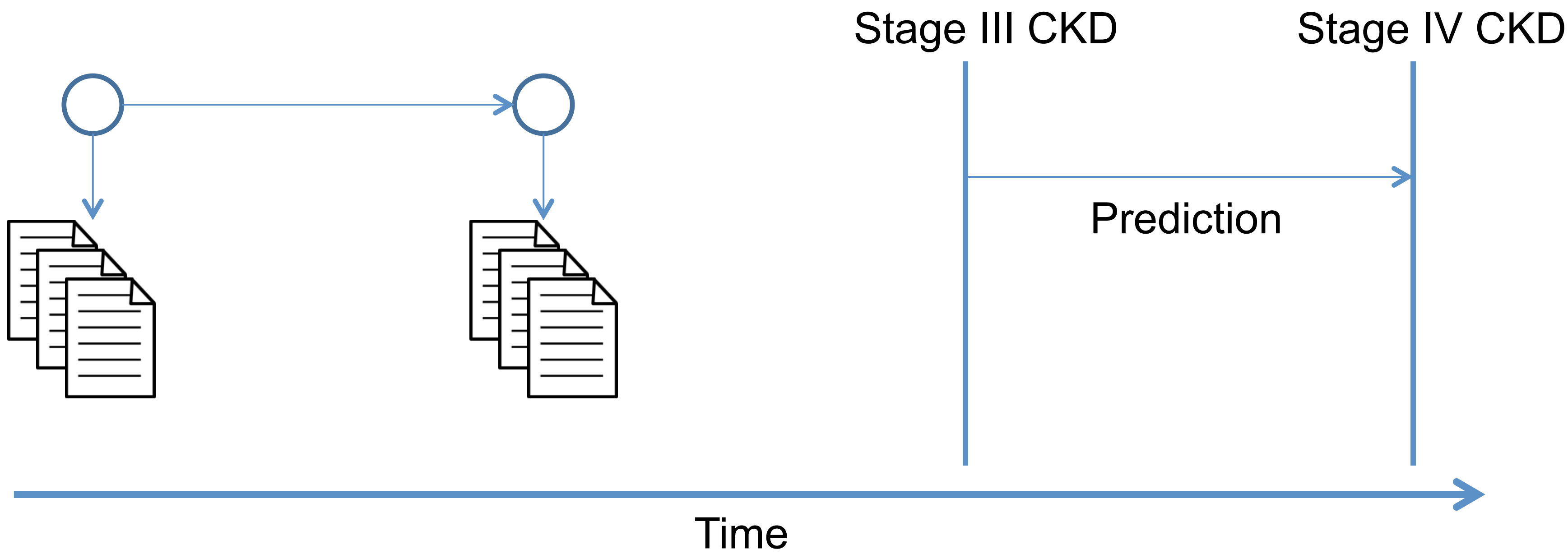
- Data
  - ~20k patients visiting primary care clinic
  - ~3k with stage III CKD and ~307 with stage IV CKD

- 5 predictive models compared – all incorporated into a basic cox
  - eGFR – Estimated glomerular filtration rate
  - RLT – Recent Laboratory tests
  - TKF – Text Kalman filter
  - LKF – Laboratory test Kalman filter
  - LTKF – Laboratory test and Text Kalman filter

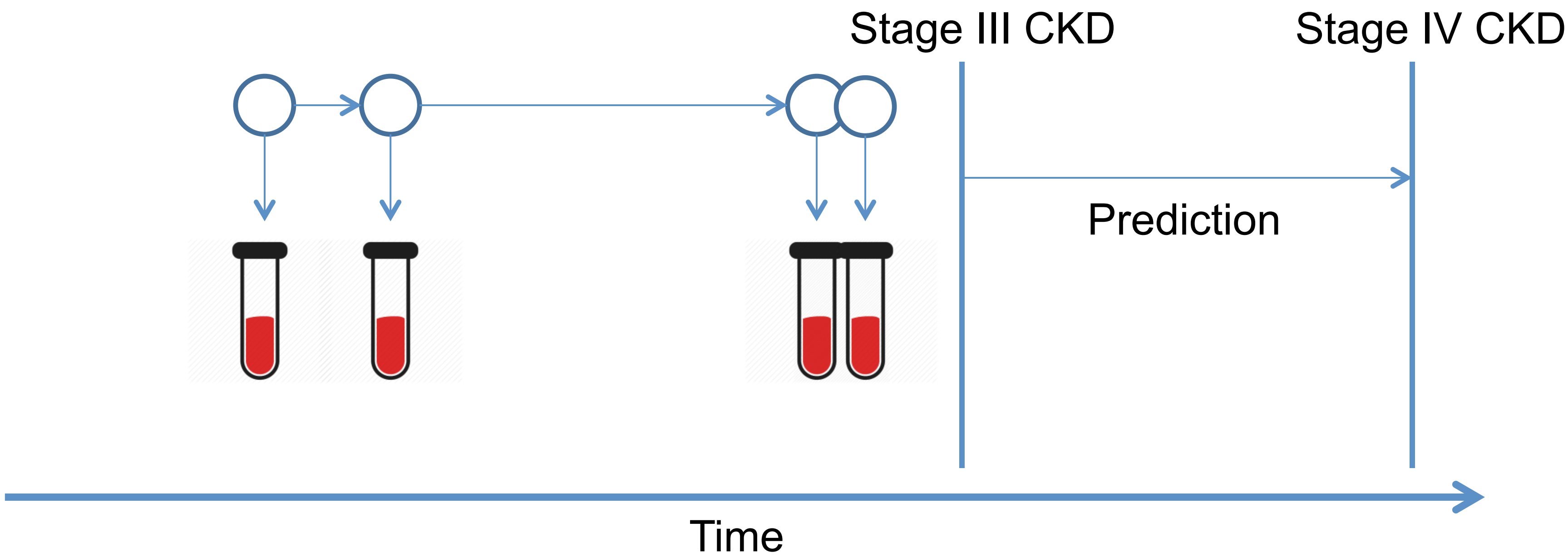
eGFR and RLT (recent lab tests) models



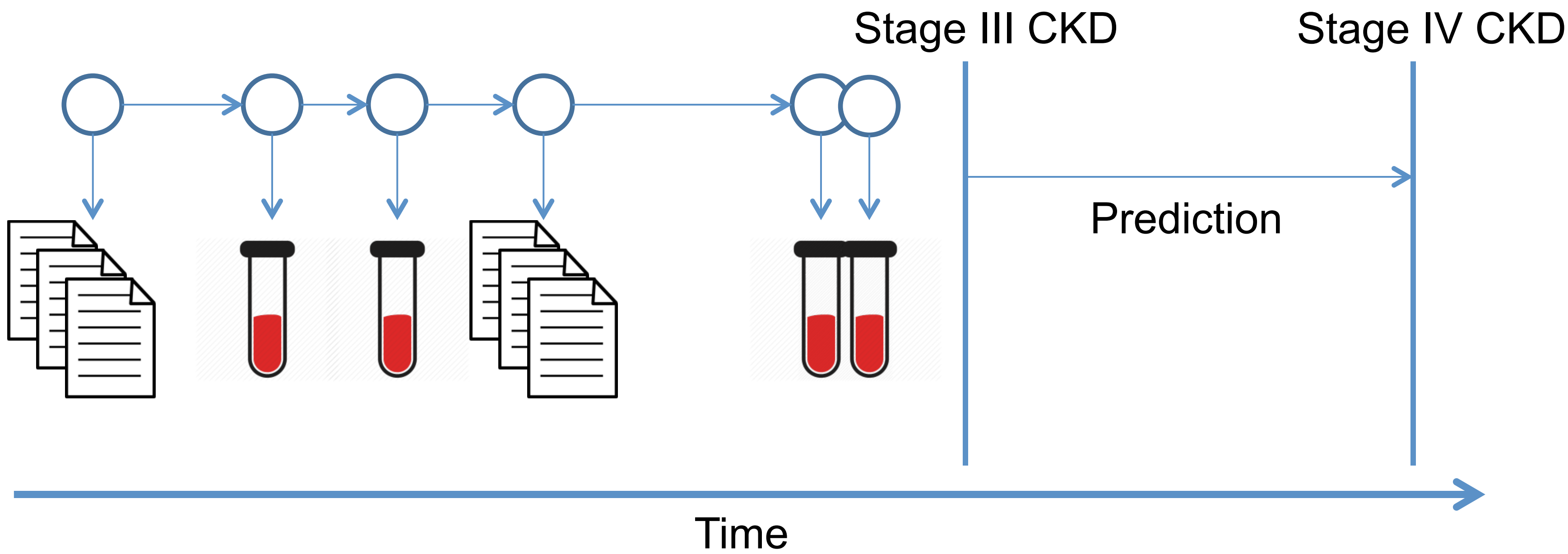
TKF (Text Kalman Filter)



LKF (Lab Kalman Filter)



LTKF (Lab & Test Kalman Filter)



Methods

- Component models
  - Model of text (latent Dirichlet allocation (LDA))
    - K=50
  - Model of the past (Kalman Filter)
    - Discrete time, binned by month, observations included 19 laboratory values and notes represented as log transformation of topic proportions
  - Model of the future (Cox proportional hazards)
    - Covariates include Kalman filter latent values at stage III onset,
      Kalman filter offsets, and demographics.
    - Dependent variable is time to stage IV

Results

	Δ LTKF	Δ LKF	Δ TKF	Δ RLT	Δ eGFR	Concordance
LTKF			***	*	***	**0.849**
LKF			***		**	0.836
TKF				***		0.733
RLT					**	0.819
eGFR						0.779

*=p<0.05, **=p<0.01, ***=p<0.001

Results – risk factors

Topic 3 (heart failure)	Topic 32 (diabetes)	Topic 29 (dialysis)
lasix	units	q15
volume	insulin	Dialysis
edema	subcutaneous	Fistula
heart	lantus	Volume
failure	glucose	Bid
worsening	diabetes	Lasix
diuresis	times	Placement
severe	70/30	Improved
diastolic	diabetic	Heparin
overload	days	Examined

Results – protective factors

Topic 33 (family history)	Topic 35 (health maintenance)	Topic 41 (non-specific)	Topic 43 (gynecological)	Topic 45 (asthma)
died	died	history	breast	Albuterol
age	flu	pressure	vaginal	Asthma
years	visit	rate	mammo	Inhaled
mother	fasting	count	cancer	Lung
father	colonoscopy	three	hx	obstructive
brother	year	revealed	pap	Wheezing
sister	shot	times	nl	Advair
worked	vaccine	shortness	age	Pulm
children	wnl	discharged	will	restrictive
deceased	check	creatinine	endometrial	Puffs

What about many diseases at once?

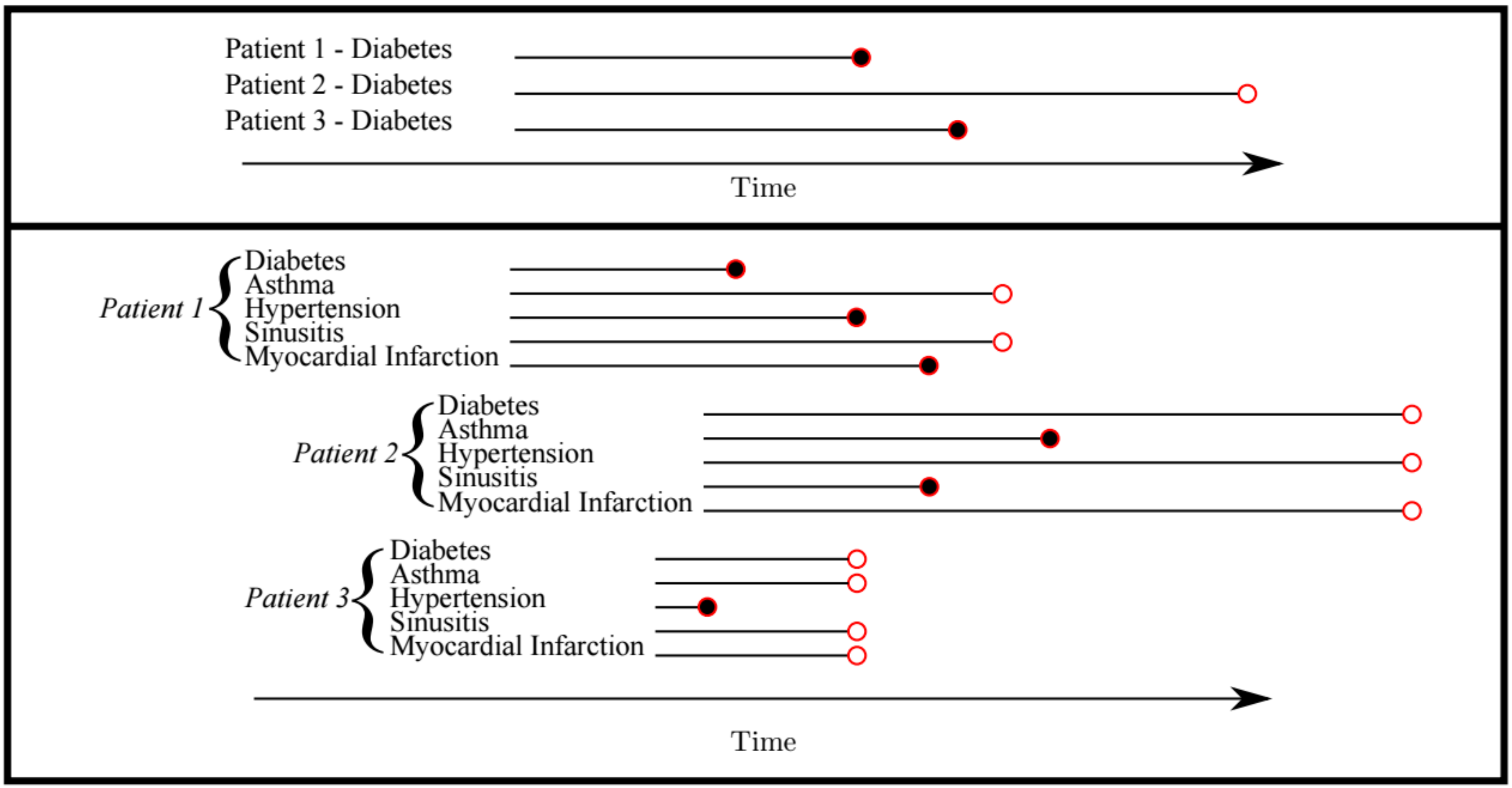


Figure 1: A comparison of standard survival analysis (top frame) and the survival filter (bottom frame). A filled circle represents an observed event, while an empty circle represents a censored one. In the case of standard survival analysis, patients in a cohort are aligned by an event. In the survival filter, patients are not aligned and unlike standard survival analysis, many conditions are considered simultaneously.

Ranganath et al (2015) The Survival Filter: Joint Survival Analysis with a Latent Time Series. UAI.

Predictive modeling on EHR data

- Incorporating longitudinal information helps
- Incorporating types of evidence (text, labs) helps

- Meaningful data science + EHR:
  - How to make this type of predictions useful for clinicians?
  - How to make them useful within their workflow?

Back to information overload

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Patient record summarization

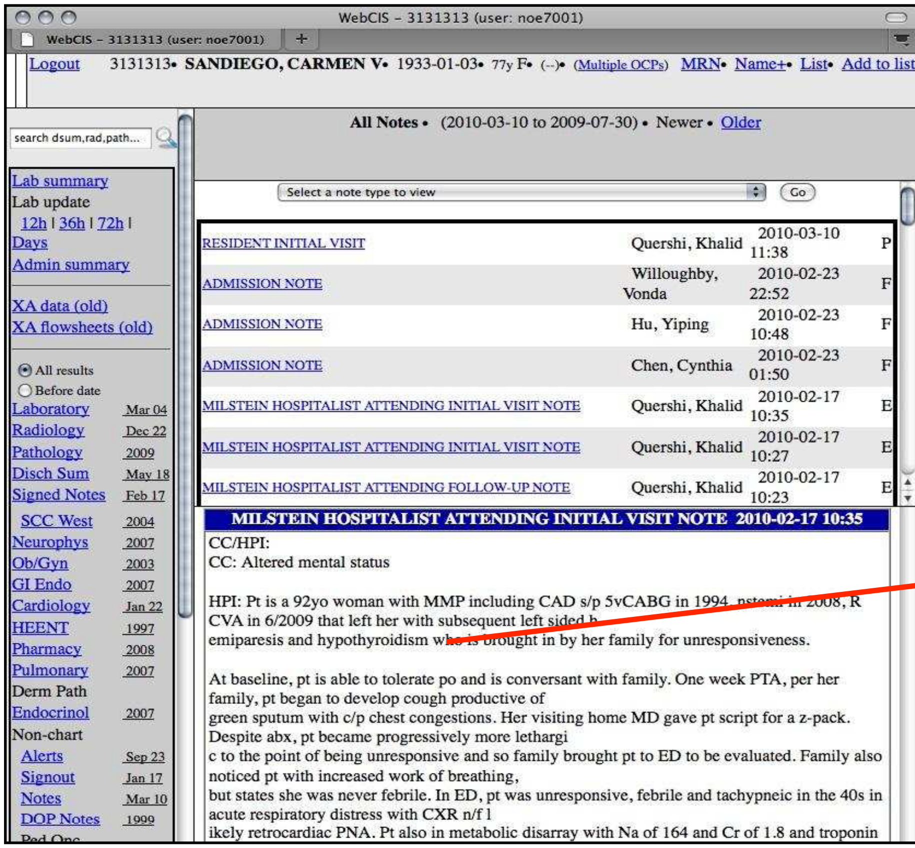
"The act of collecting, distilling, and synthesizing patient information for the purpose of facilitating any of a wide range of clinical tasks"

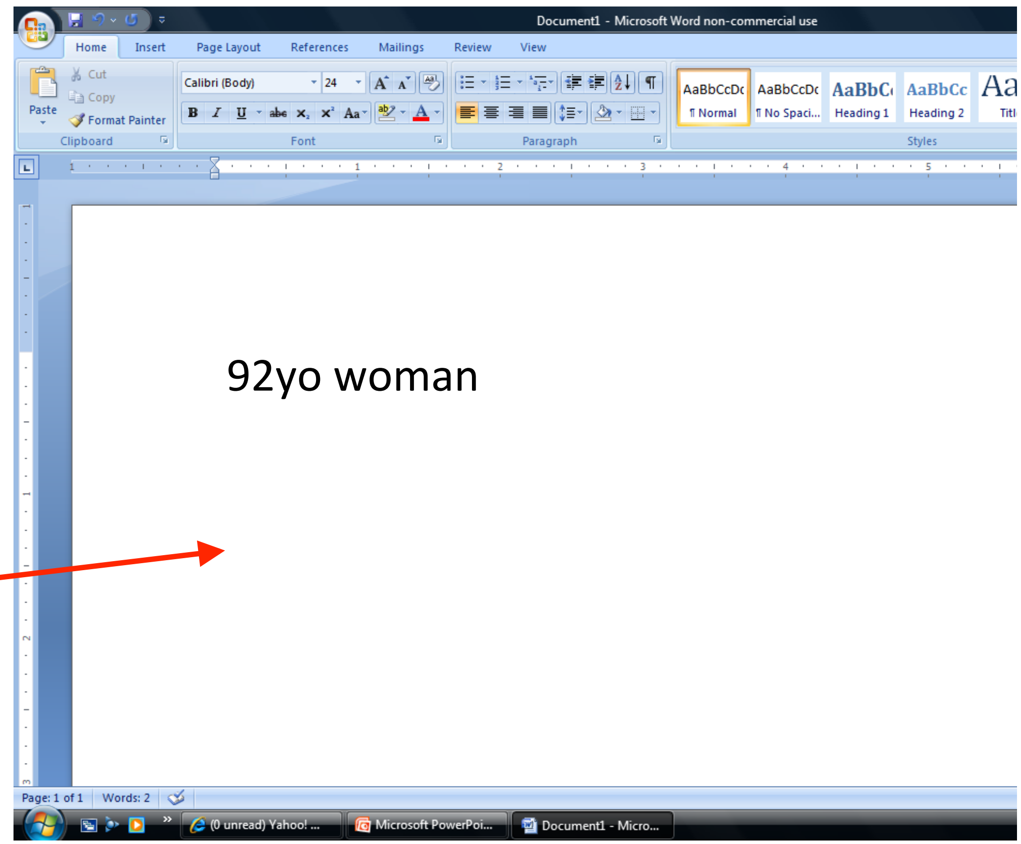
Previous approaches

- focus on specific disease
- focus on specific care setting (ICU)
- largely ignore EHR text
- deployment and study of impact is lacking

Flebowitz et al (2011) Summarization of clinical information: a conceptual model. J Biomed Inform.
Pivovarov and Elhadad (2015) Automated methods for summarization of electronic health records. J Am Med Inform.

How clinicians summarize patient information

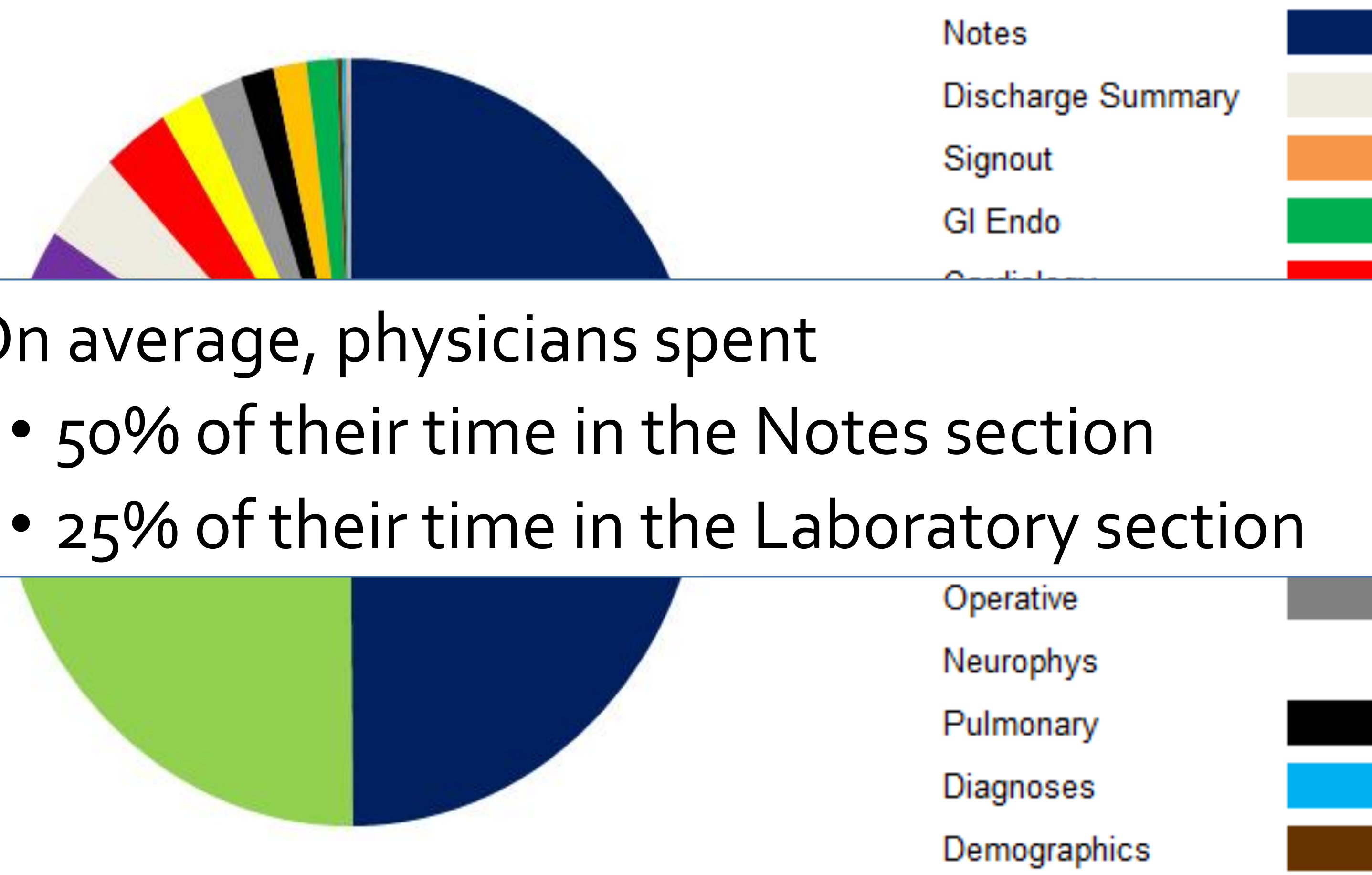




Reichert et al (2010) Cognitive analysis of the summarization of longitudinal patient records. AMIA Annu Symp.

How clinicians summarize patient information

Average time in each section of the EHR

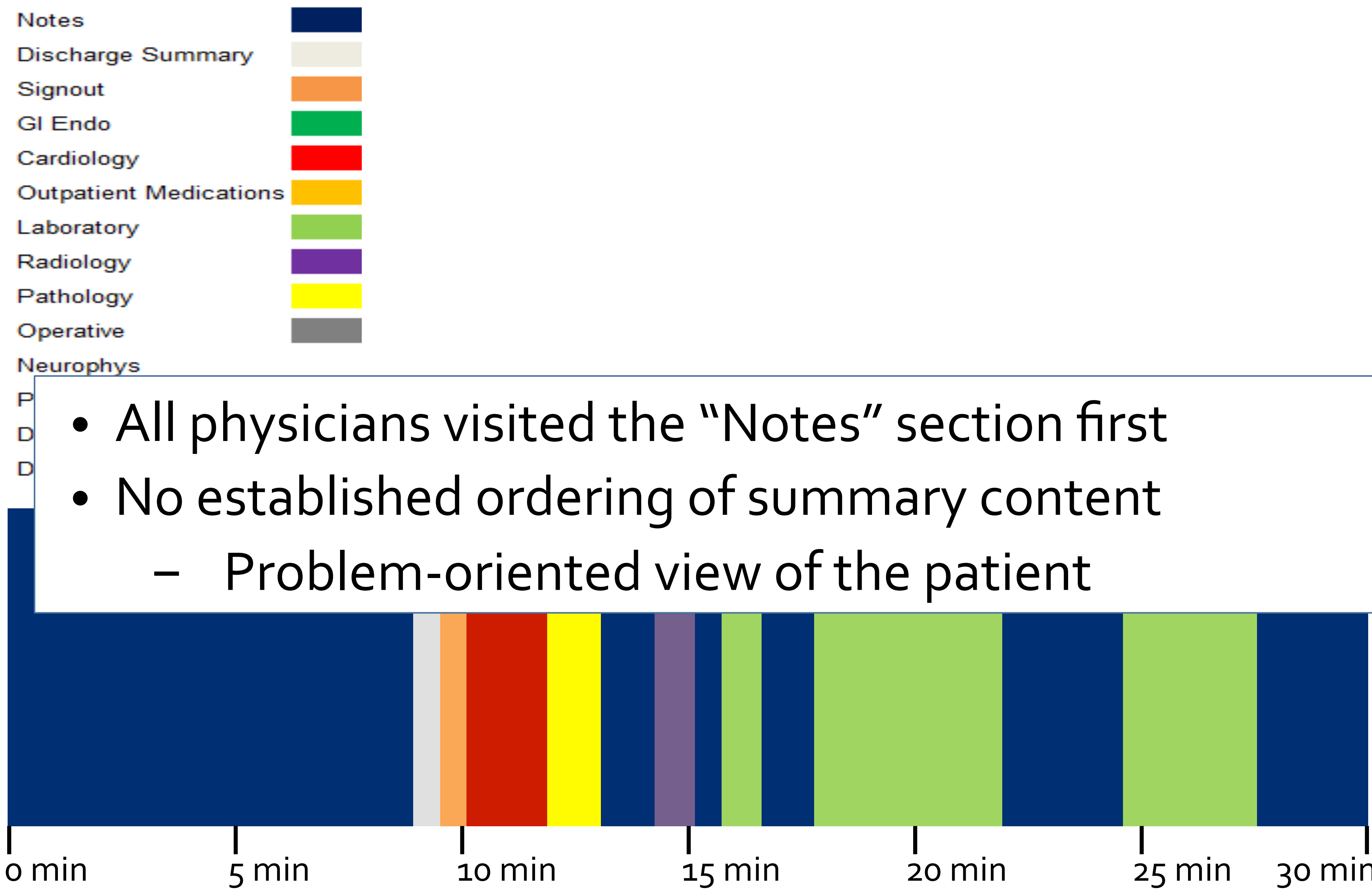


On average, physicians spent

- 50% of their time in the Notes section
- 25% of their time in the Laboratory section

Reichert et al (2010) Cognitive analysis of the summarization of longitudinal patient records. AMIA Annu Symp.

How clinicians summarize patient information



- All physicians visited the “Notes” section first
- No established ordering of summary content
  - Problem-oriented view of the patient

Reichert et al (2010) Cognitive analysis of the summarization of longitudinal patient records. AMIA Annu Symp.

Functionality wish list for an EHR summarizer

- Aggregate information from the whole record
- But allow for zooming in and out of particular parts of the record
- Use notes as primary content selection source
- Facilitate finding supporting evidence in documentation
- Be problem oriented
- Be interactive
- Update in “real time”

HARVEST

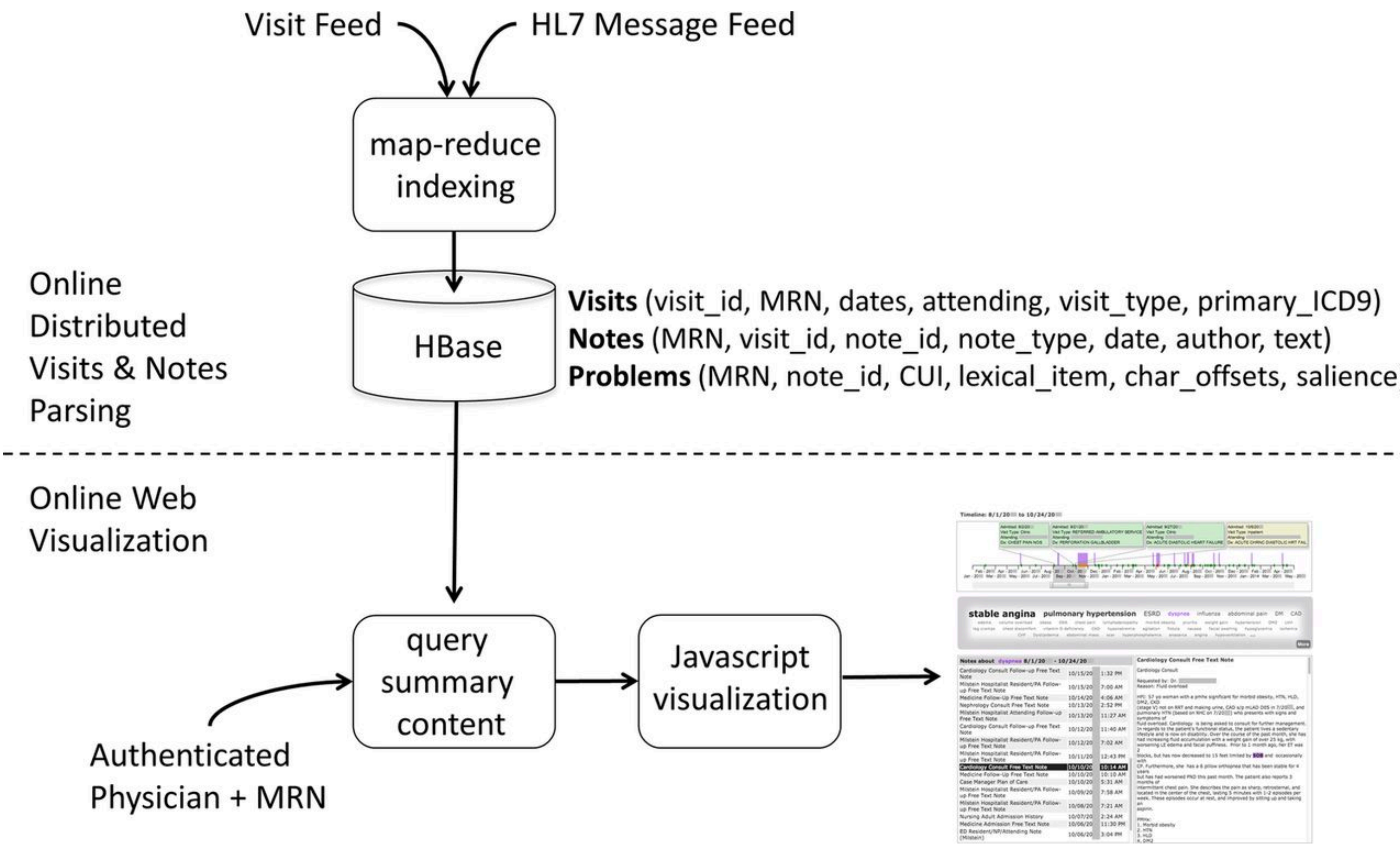
- Extracts content from a patient's longitudinal documentation
- Aggregates information from multiple care settings
- Visualizes content through a timeline of a patient's problem documentation and clinical encounters

- Distributed computing infrastructure
- Deployed at NewYork-Presbyterian hospital

- local harvest

Hirsch et al (2015) HARVEST, a longitudinal patient record summarizer. J Am Med Inform Assoc.

HARVEST


Visit Feed
HL7 Message Feed
map-reduce indexing
Online Distributed Visits & Notes Parsing
HBase
Visits (visit_id, MRN, dates, attending, visit_type, primary_ICD9)
Notes (MRN, visit_id, note_id, note_type, date, author, text)
Problems (MRN, note_id, CUI, lexical_item, char_offsets, salience)
Online Web Visualization
query summary content
Javascript visualization
Authenticated Physician + MRN
stable angina
pulmonary hypertension

Natural language processing of clinical documentation

- Extract problems mentioned in all the notes of a record
  - Conditions, as well as signs and symptoms
- Compute salience of problem documentation for a given time frame in a patient record

- Challenges
  - Robust processing across all note types
  - Identify and merge problems that are semantically similar
  - Handle redundancy within longitudinal record

Pivovarov & Elhadad (2012) A hybrid knowledge-based and data-driven approach to identifying semantically similar concepts. J Biomed Inform.

Cohen et al (2013) Redundancy in electronic health record corpora: analysis, impact on text mining performance, and mitigation strategies. BMC Bioinform.

Cohen et al (2014) Redundancy-Aware Latent Dirichlet Allocation for Patient Record Notes. PloS ONE.

Hirsch et al (2014) HARVEST, a longitudinal patient record summarizer. J Am Med Inform Assoc.

Natural language processing of clinical documentation

- Distributed infrastructure
  - 650,000 notes/month avg. are authored at NYP
  - 20,000 notes/second parsing and indexing
    (compared to 500 notes/second in a non-distributed infrastructure)

Use cases

- "What's the story?"
  - ED visit
  - Hospital admission
  - Walk-in at clinic
- Quality indicators
  - 2-hour on average per patient
  - HARVEST use shortens chart review by 20 mins on average (log analysis) and increases confidence of abstraction (survey)
- Researchers and trial coordinators
- Education

Next steps

- How to handle
  - Not mentions in documentation, but actual presence of a condition, based on all EHR observations
  - Conditions not diagnosed yet, but documentation supports their presence
- Need a mechanism to describe the presence of a disease for any time slice of a patient record

Disease modeling

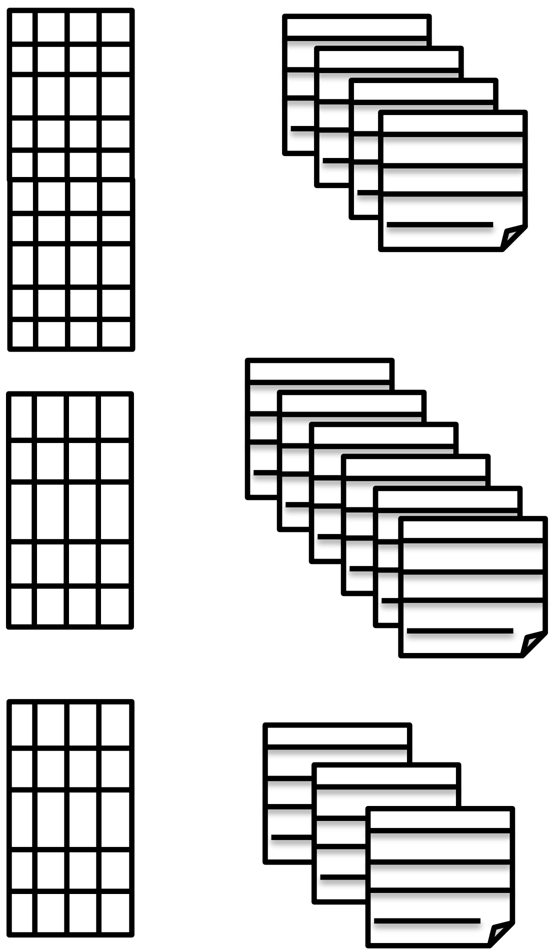
- Isn't there a list of problems somewhere in the EHR we can look up?
  - There are manually curated problem lists, but not guarantee they are filled or maintained by clinicians
  - Doesn't handle yet-to-be diagnosed conditions
- Couldn't we ask clinicians to describe each disease as a set of patient characteristics and go from there?
  - eMERGE PheKB
  - 42 diseases phenotyped so far

Phenotyping wish list

- Portable across institutions
- Data-Driven
- Not expert intensive
- Probabilistic
- Robust to very large datasets
- Robust to many diseases (up to 1000)
- Robust to many patients

Large-scale, probabilistic phenotyping

Patient Records
Structured and Unstructured

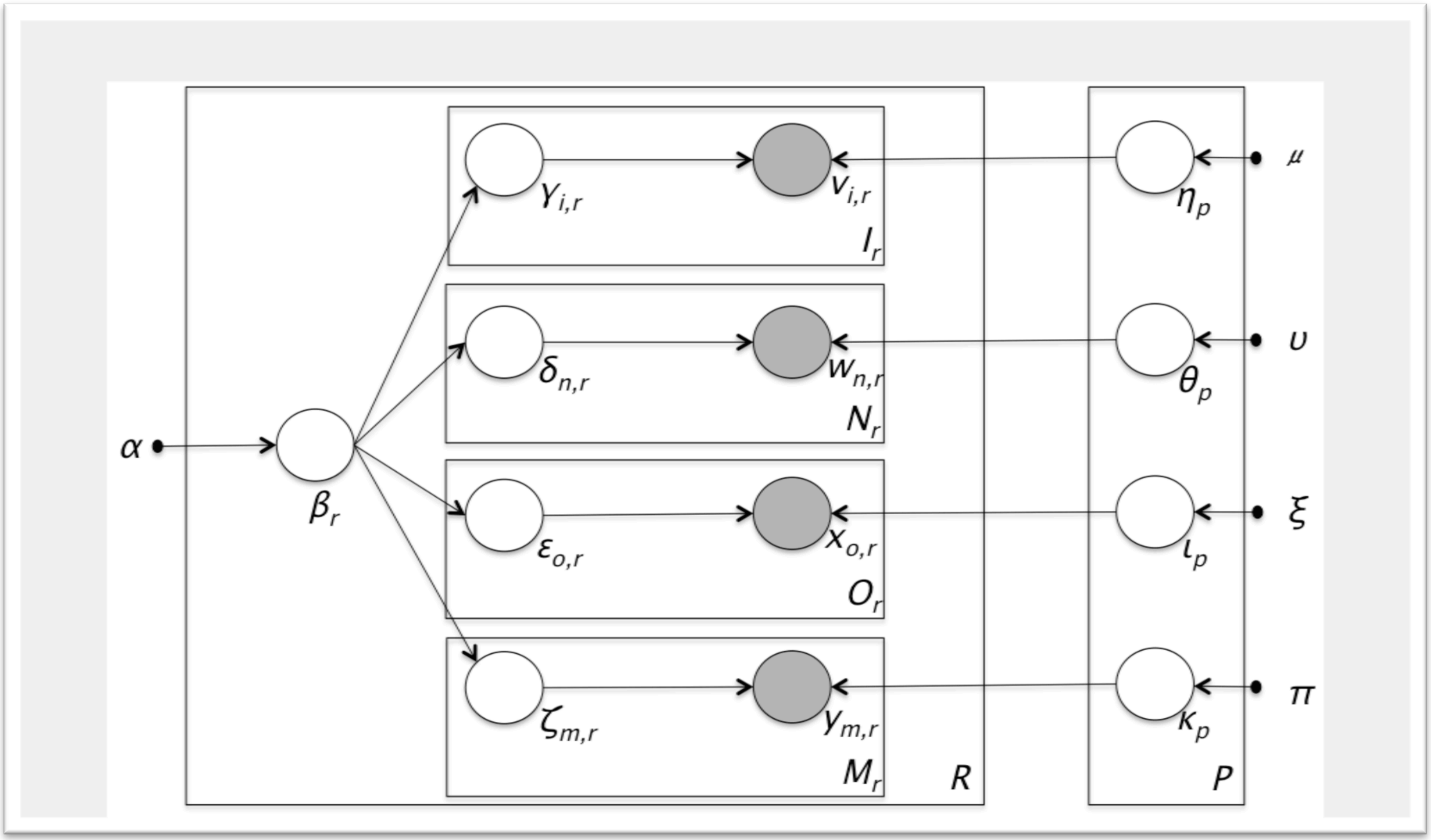


Learned Probabilistic phenotypes

Diabetes Mellitus
Congestive Heart Failure
Depressive Disorder
Joint Disorder
Lupus
Chronic Kidney Disease
Breast Cancer
Colon Cancer
Asthma
Hyperlipidemia
...

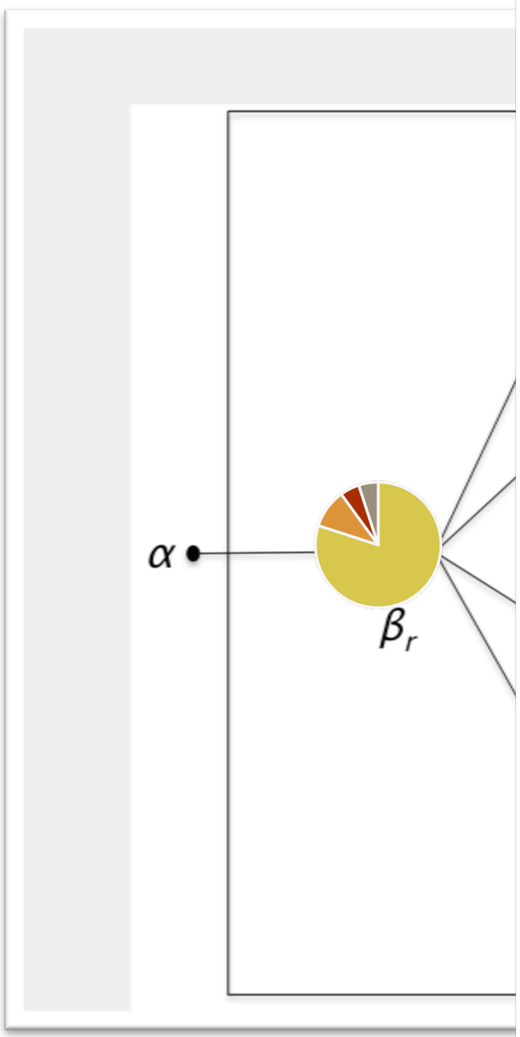
Inference mechanism

Uphenome (unsupervised)

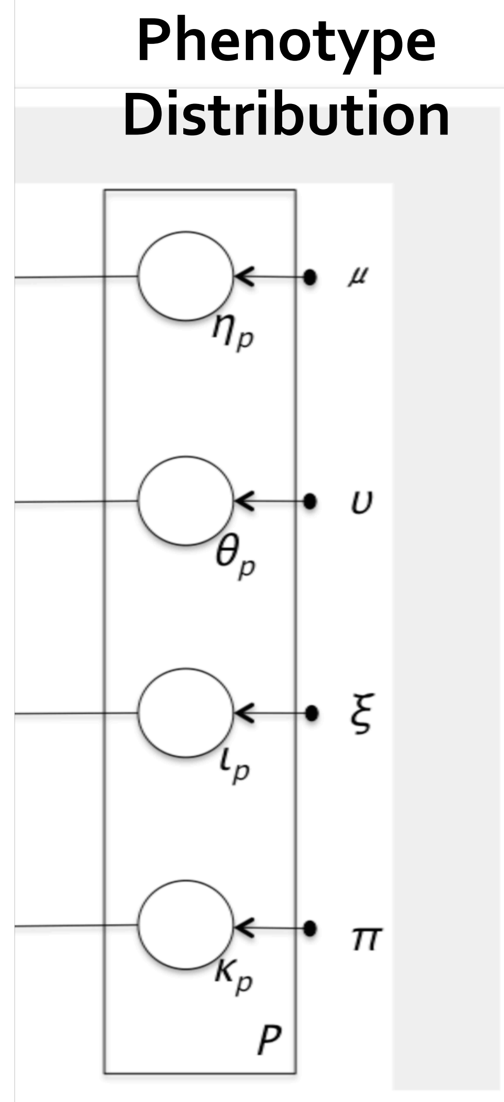


Uphenome (unsupervised)

Patient phenome



Uphenome (unsupervised)



Experimental Data

Can we learn phenotypes across institutions and care settings?

	MIMIC - ICU Total / Unique	**NYPH - Outpatient Total / Unique**
Patients	*18,697 / 18,697*	*9,828 / 9,828*
Words	13,086,278 /12,919	13,494,149 /13,158
Medications	1,044,541 / 855	9,978 / 273
Lab Tests	7,499,446 / 309	351,992 / 300
Diagnoses	159,740 / 985	177,420 / 931

Experiments

- How good are the learned phenotypes
  - Physician-rated phenotype coherence
  - Physician-rated phenotype granularity
  - Physician-rated phenotype comparison to baseline (LDA-all)

- How ell does the model infer phenotypes for unseen patients
  - Compare learned phenotypes to gold-standard annotations in notes

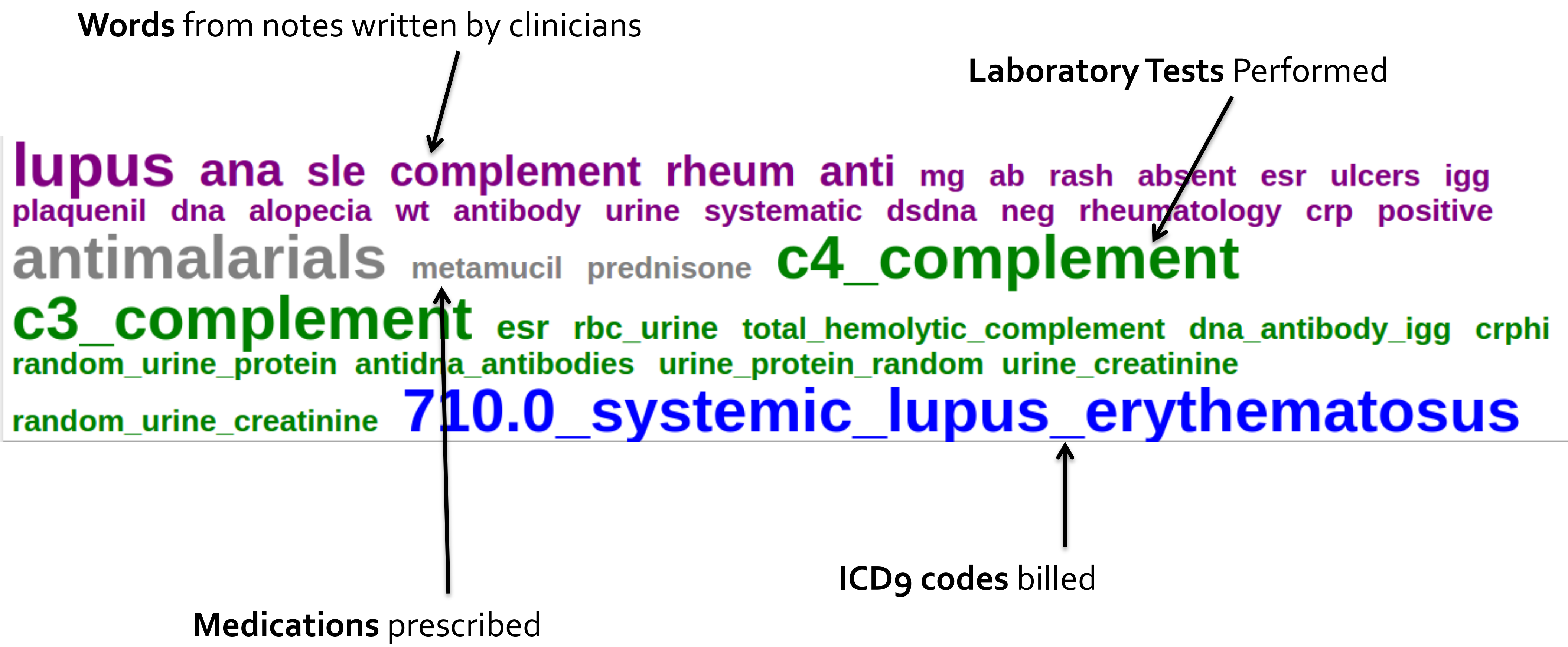
Experimental setup

80% of data used for training set, 20% for test set

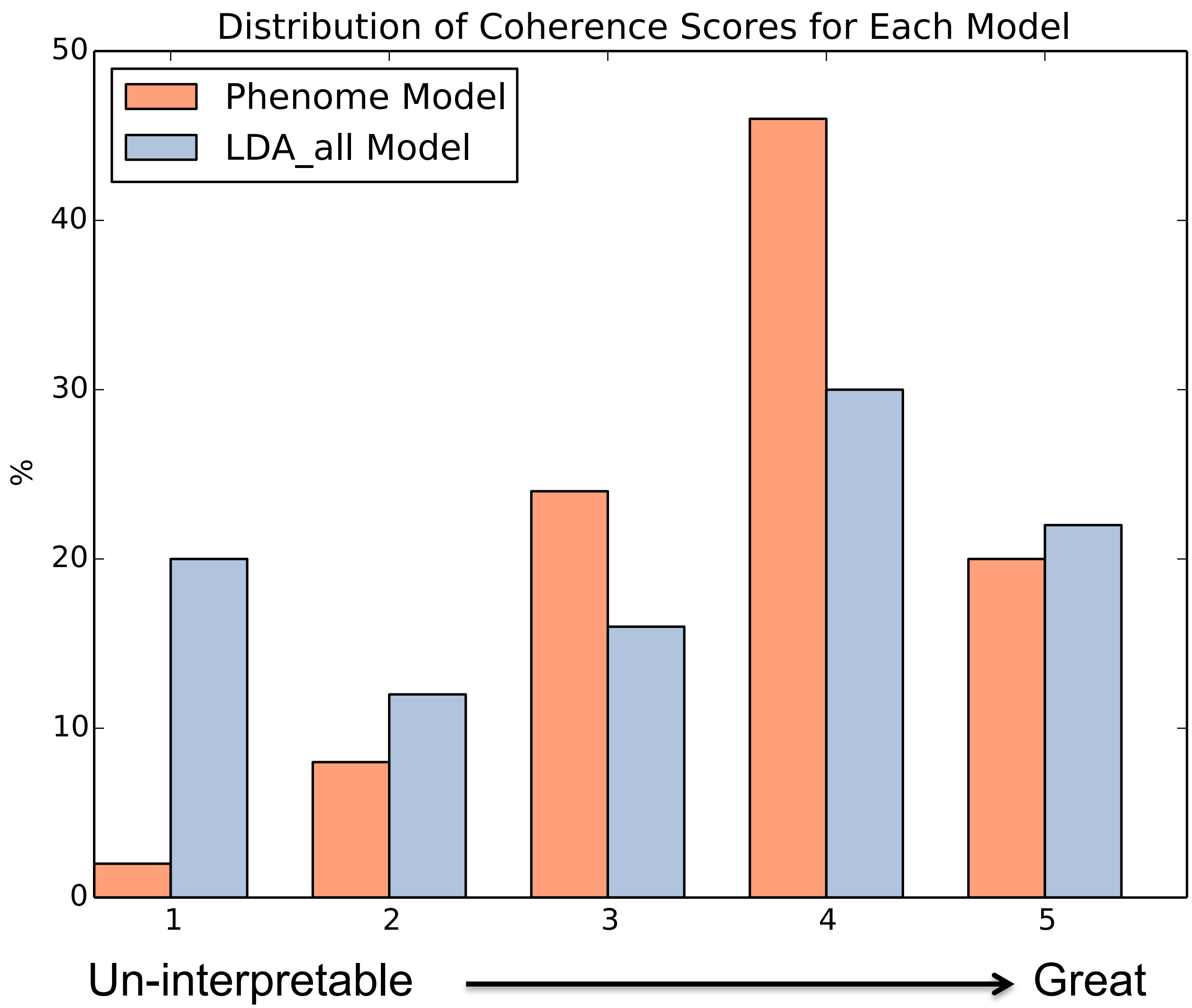
Parameters

- P=250
- $\alpha = 0.1$
- $\mu, \nu, \xi, \pi = 0.1$
- # training Gibbs sampling iterations = 7,000
- # testing Gibbs sampling iterations = 1,000

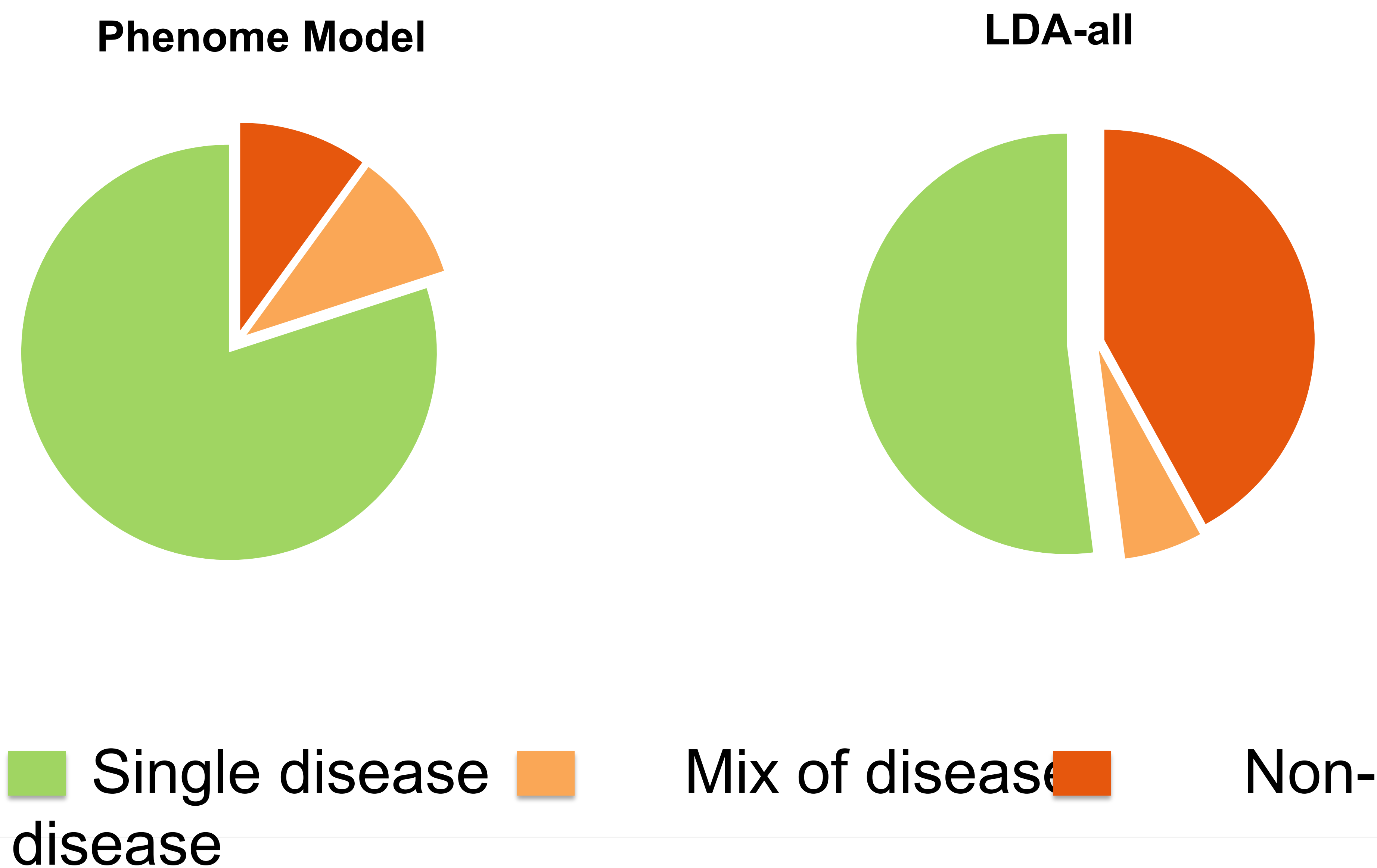
Phenotype example



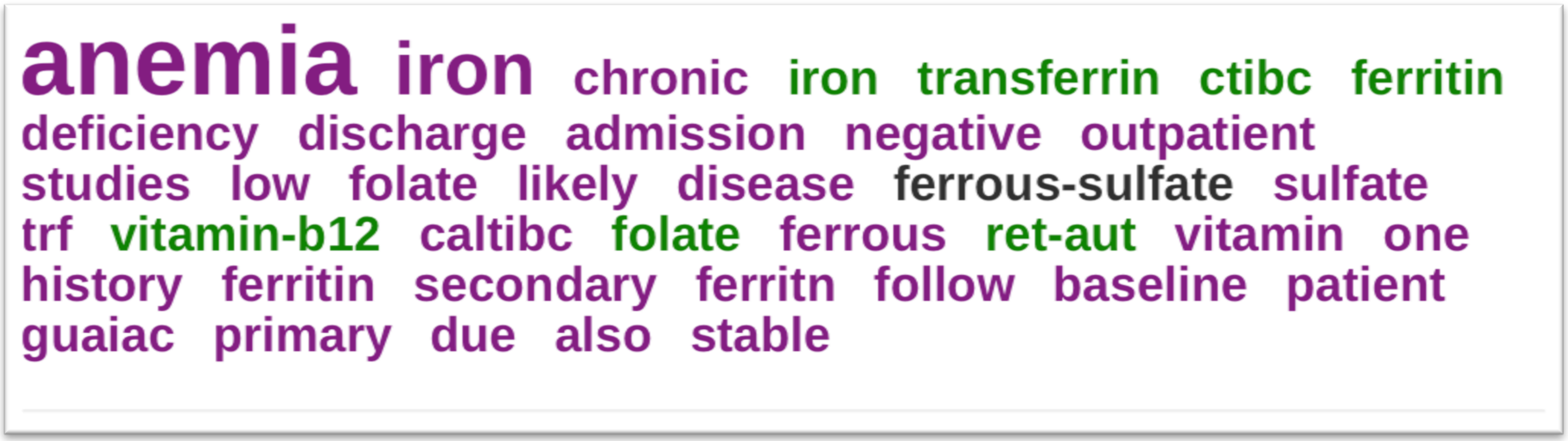
Results – coherence

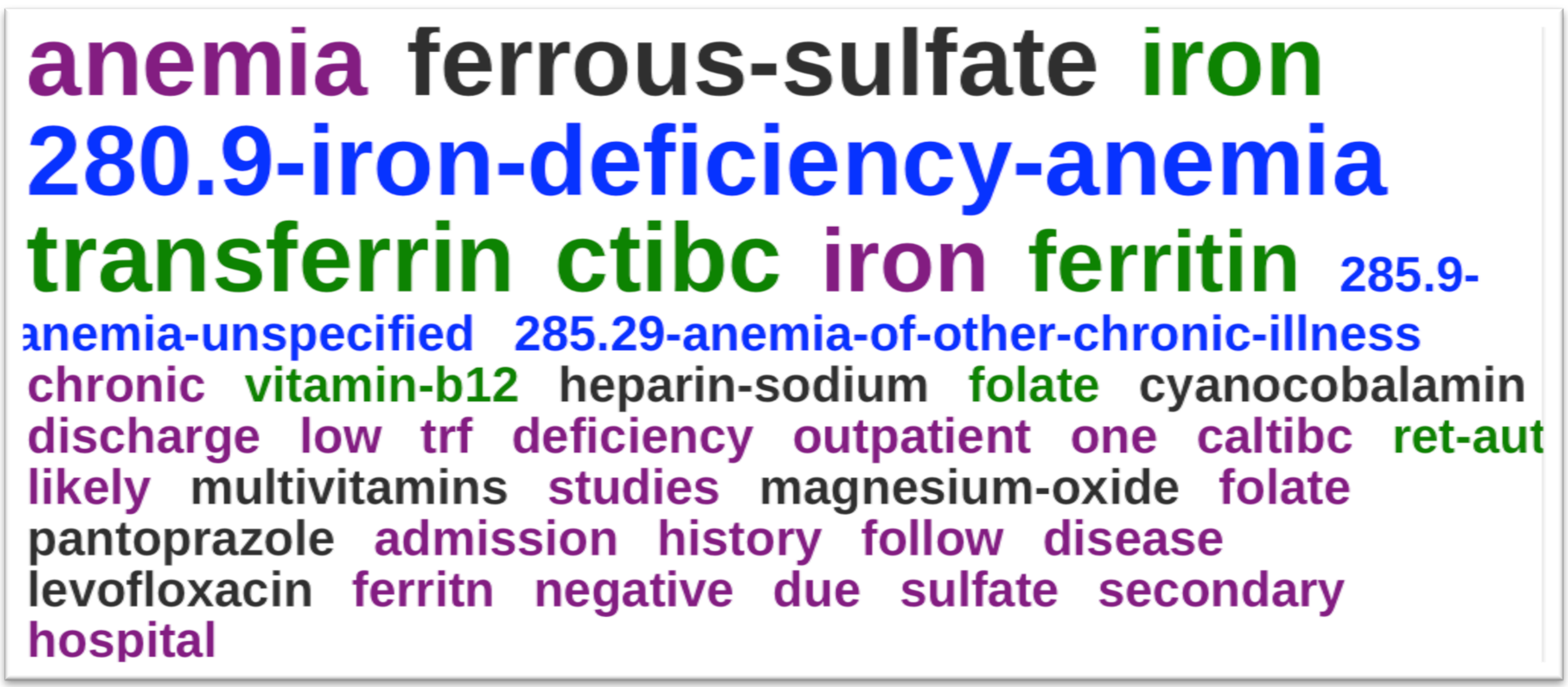


Results – granularity



Results – comparison to baseline





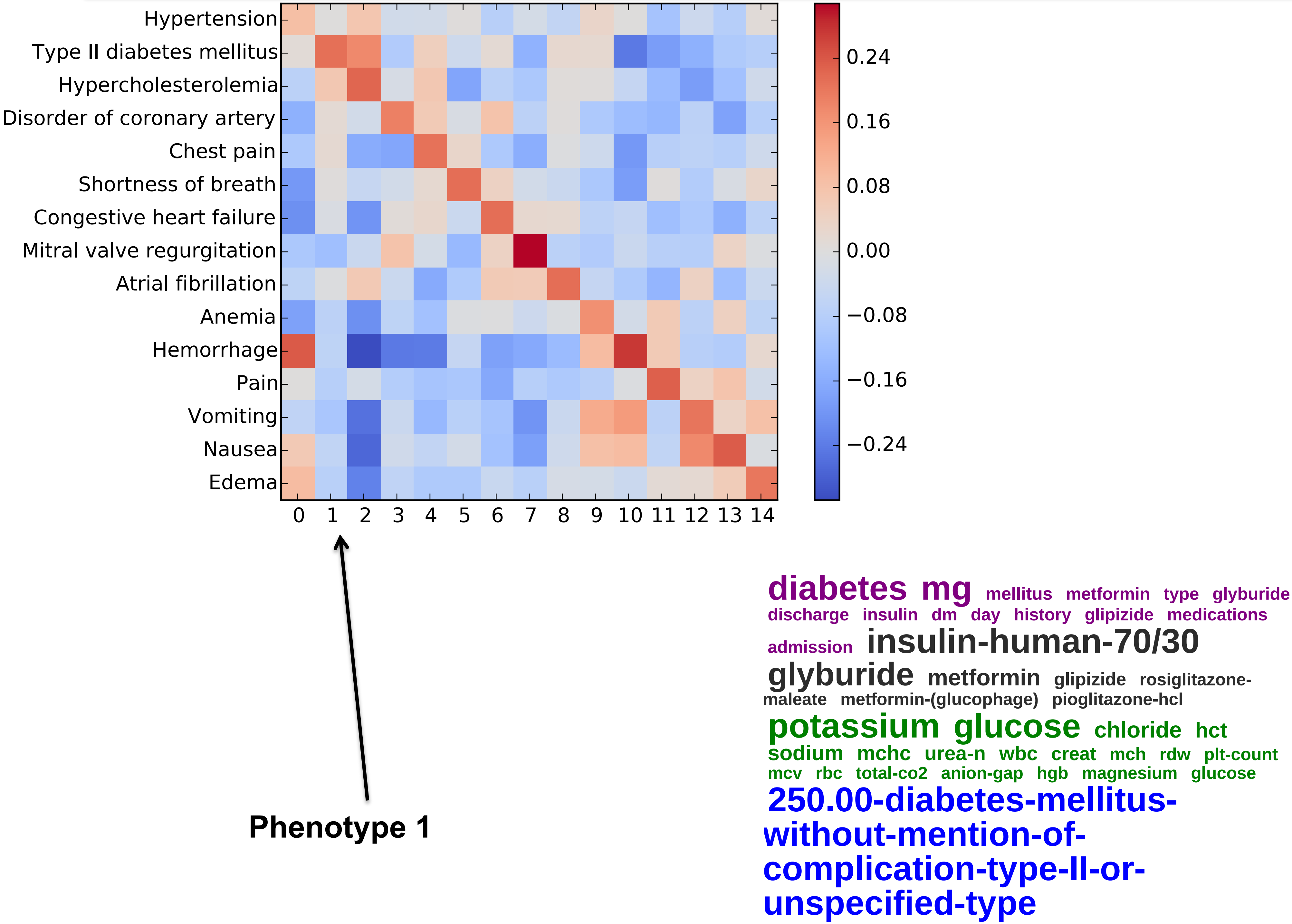
80.4 %
of the time,
the Phenome
model was
preferred

Results – inference on unseen patients

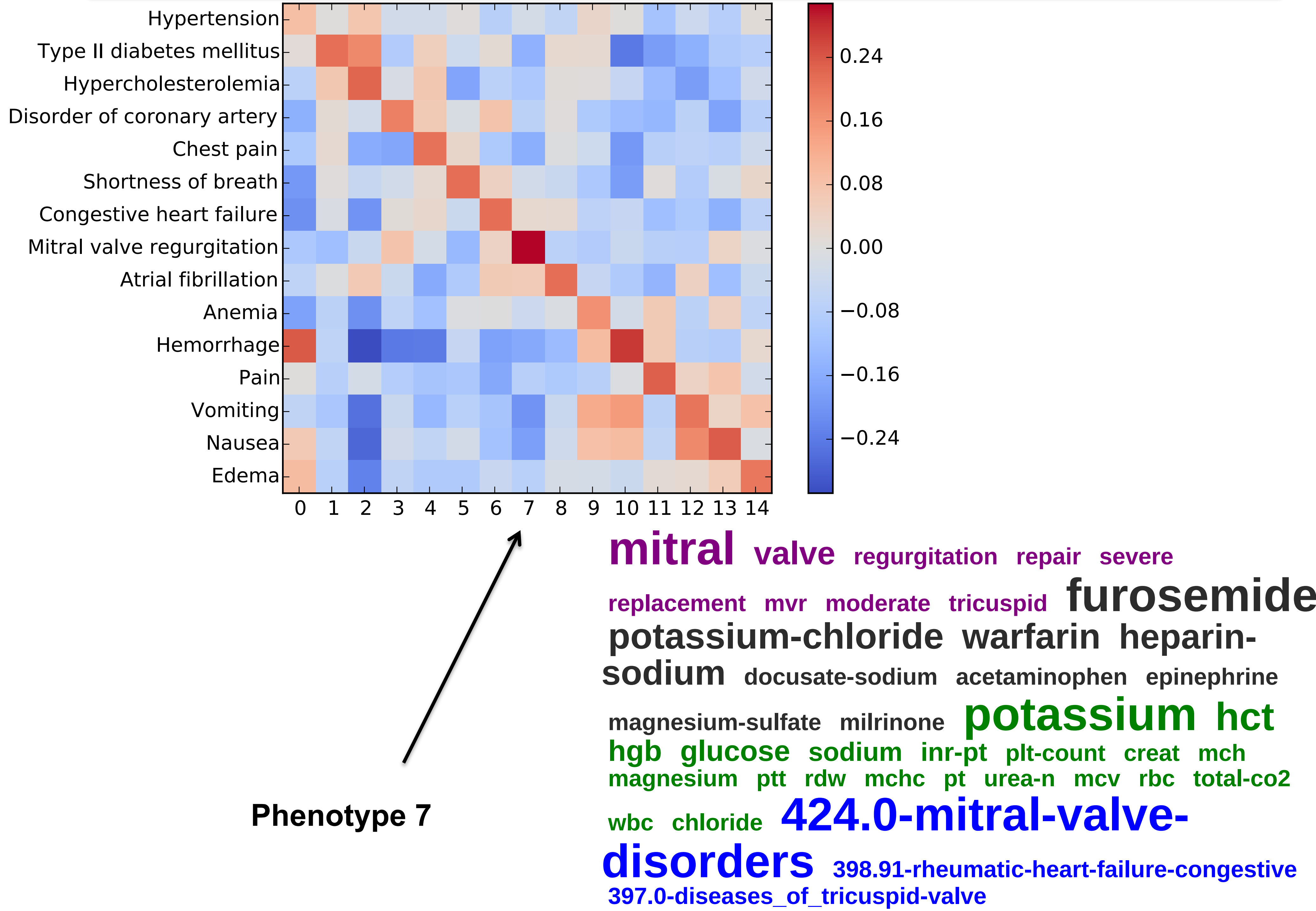
Disorders that appear in a patient record
(assigned to patient, not negated, not generic)

vs.

Phenotypes that are inferred for that patient



Hypertension
Type II diabetes mellitus
Hypercholesterolemia
Disorder of coronary artery
Chest pain
Shortness of breath
Congestive heart failure
Mitral valve regurgitation
Atrial fibrillation
Anemia
Hemorrhage
Pain
Vomiting
Nausea
Edema
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
0.24
0.16
0.08
0.00
−0.08
−0.16
−0.24
Phenotype 1
diabetes mg mellitus metformin type glyburide discharge insulin dm day history glipizide medications admission
insulin-human-70/30 glyburide metformin glipizide rosiglitazone-maleate metformin-(glucophage) pioglitazone-hcl
potassium glucose chloride hct sodium mchc urea-n wbc creat mch rdw plt-count mcv rbc total-co2 anion-gap hgb magnesium glucose
250.00-diabetes-mellitus-without-mention-of-complication-type-II-or-unspecified-type


Hypertension
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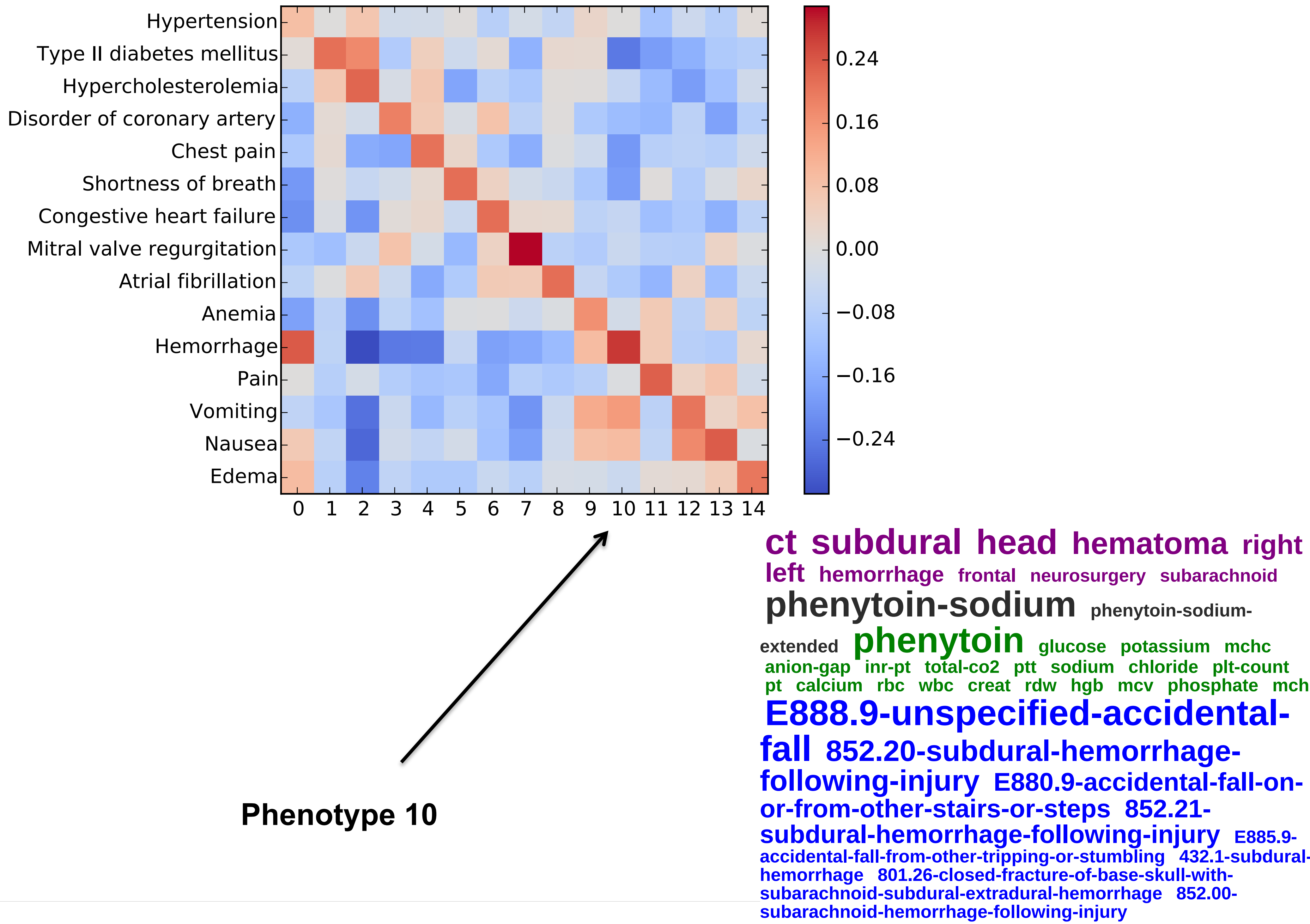
Congestive heart failure
Mitral valve regurgitation
Atrial fibrillation
Anemia
Hemorrhage
Pain
Vomiting
Nausea
Edema
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
0.24
0.16
0.08
0.00
−0.08
−0.16
−0.24
Phenotype 7
mitral valve regurgitation repair severe
replacement mvr moderate tricuspid furosemide
potassium-chloride warfarin heparin-sodium docusate-sodium acetaminophen epinephrine
magnesium-sulfate milrinone potassium hct
hgb glucose sodium inr-pt plt-count creat mch
magnesium ptt rdw mchc pt urea-n mcv rbc total-co2
wbc chloride 424.0-mitral-valve-disorders 398.91-rheumatic-heart-failure-congestive
397.0-diseases_of_tricuspid-valve



Hypertension
Type II diabetes mellitus
Hypercholesterolemia
Disorder of coronary artery
Chest pain
Shortness of breath
Congestive heart failure
Mitral valve regurgitation
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Nausea
Edema
0 1 2 3 4 5 6 7 8 9 10 11 12 13 14
0.24
0.16
0.08
0.00
−0.08
−0.16
−0.24
Phenotype 10
ct subdural head hematoma right left hemorrhage frontal neurosurgery subarachnoid
phenytoin-sodium phenytoin-sodium-extended
phenytoin glucose potassium mchc anion-gap inr-pt total-co2 ptt sodium chloride plt-count pt calcium rbc wbc creat rdw hgb mcv phosphate mch
E888.9-unspecified-accidental-fall 852.20-subdural-hemorrhage-following-injury E880.9-accidental-fall-on-or-from-other-stairs-or-steps 852.21-subdural-hemorrhage-following-injury E885.9-accidental-fall-from-other-tripping-or-stumbling 432.1-subdural-hemorrhage 801.26-closed-fracture-of-base-skull-with-subarachnoid-subdural-extradural-hemorrhage 852.00-subarachnoid-hemorrhage-following-injury

Conclusions

- Disease modeling
  - Leveraging heterogeneous data helps, but need for appropriate models
- EHR summarization
  - Robust NLP of underlying data
  - Information visualization
  - Computing infrastructure to enable operational summarization
- Virtuous circle

Thank you!

`people.dbmi.columbia.edu/noemie/phenosum`

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National Science Foundation award #1344668