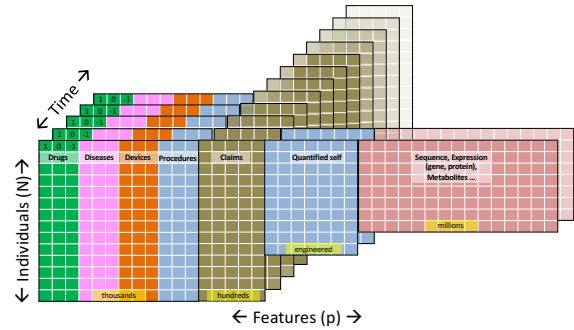


EMR Data mining

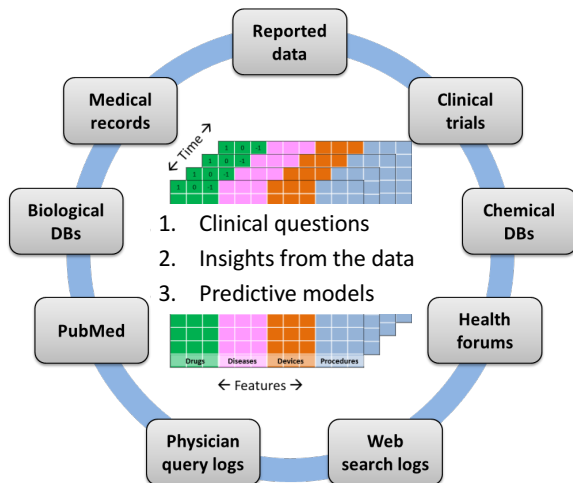
Nigam Shah
nigam@stanford.edu



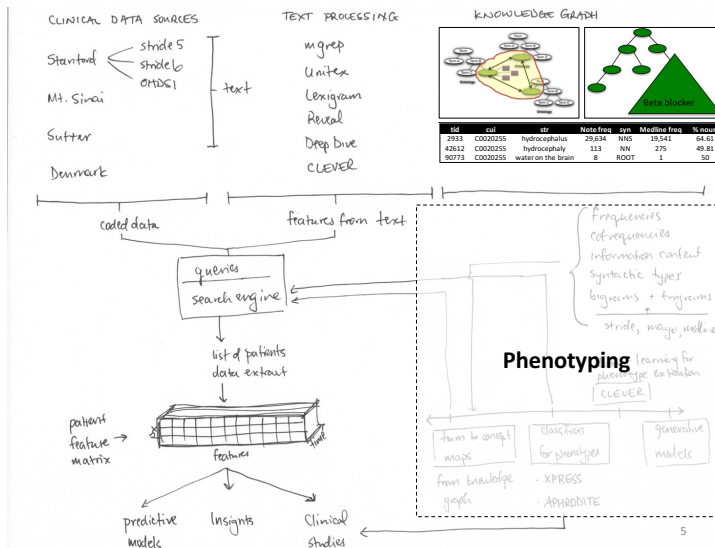
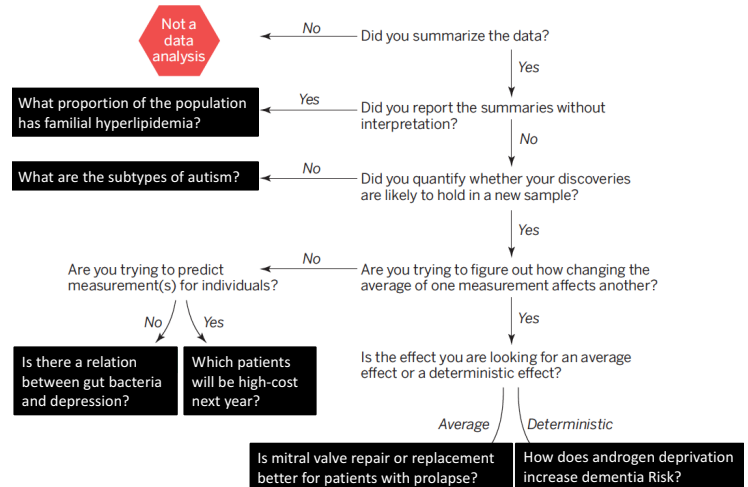
The Data and the problem



We do a lot, without knowing what works.

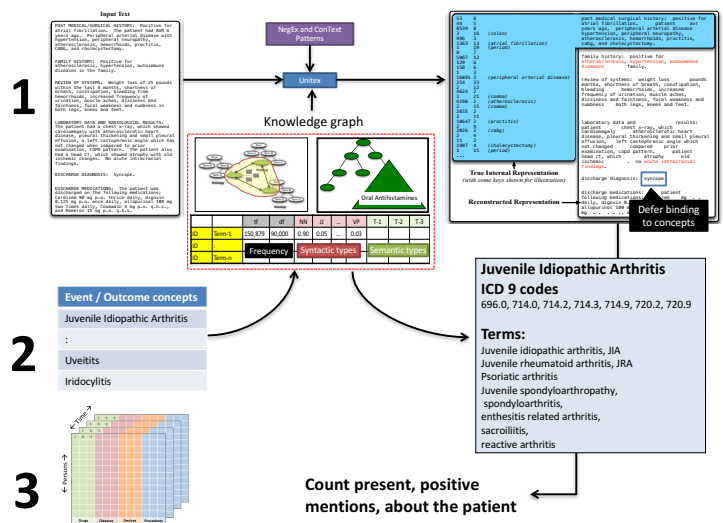
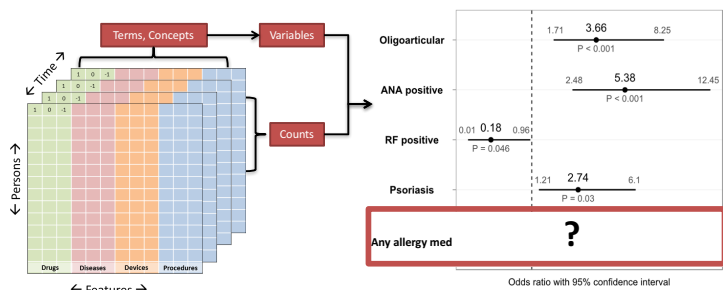


Understanding the question

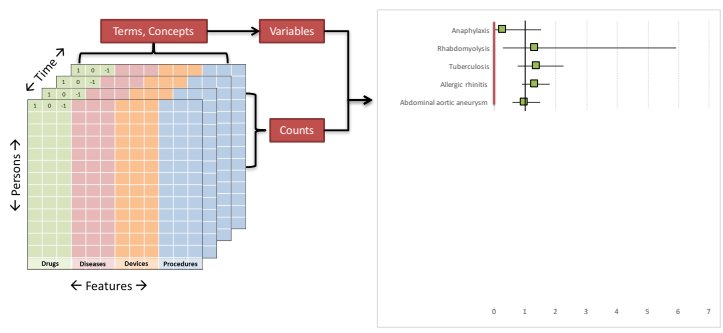


Clinical studies

Profiling risk factors for chronic uveitis

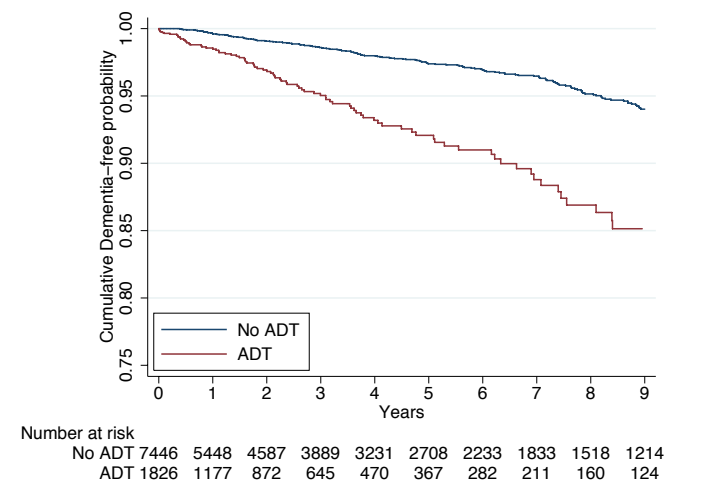


Androgen deprivation & Alzheimer's risk



www.tinyurl.com/JCO-ADT

Androgen deprivation & Dementia risk



Searching 1,459,052 patients over 11,950,995 encounters

46

54

M

F

GENDER

42

9

3

46

White

Asian

Black

Other

RACE

24

37

24

15

18

19-44

45-64

65+

AGE

QUERY

```
// patients with cryptogenic stroke, where we don't have an obvious reason for the stroke
var stroke = Intersect(OR(icd9=436, icd9=434), NOT(OR(icd9=393, icd9=394, icd9=397.1, icd9=397.9, icd9=398, icd9=246, icd9=424.9, icd9=V43, icd9=433.1, icd9=431, icd9=434.11, icd9=434.01)), AGE (40 years, 90 years), VISIT TYPE="INPATIENT", NOT(TEXT="thyroid diseases"), NOT(TEXT="heart valve prosthesis"), NOT(TEXT="disease of mitral valve"), NOT(TEXT="rheumatic heart disease"))

// those that got diagnosed with Afib
var afib = FIRST_MENTION(icd9=427.31)

// those that had a cryptogenic stroke, and got diagnosed with Afib in 1 to 5 years
BEFORE ($stroke*, $afib)+(-5 years, -1 year)
```

VARS: MINE GROUP

234 patients 0.305 s

DOWNLOAD DATASET

Cohort is male, white and 65+ years old

53

46

47

34

M

F

GENDER

39

9

6

4

2

54

65

White

Asian

Black

Other

0-18

19-44

45-65

65+

AGE

Mostly 1-10 encounters, lasting 1-50 months

10

15

15

18

3

5

10

11-20

21-30

31+

ENCOUNTERS

77

24

11

29

5

20

1-50

51-99

100-149

150+

DURATION (MONTH)

ICD9

% cohort/general

434.91

Ctbi art ocl NOS w infrc

79

1

100

CPT

% cohort/general

70450

Ct head/brain w/o dye

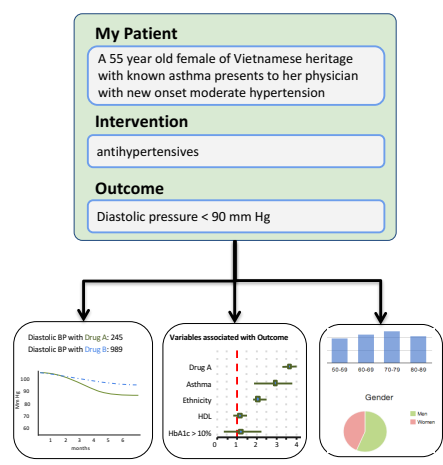
62

2

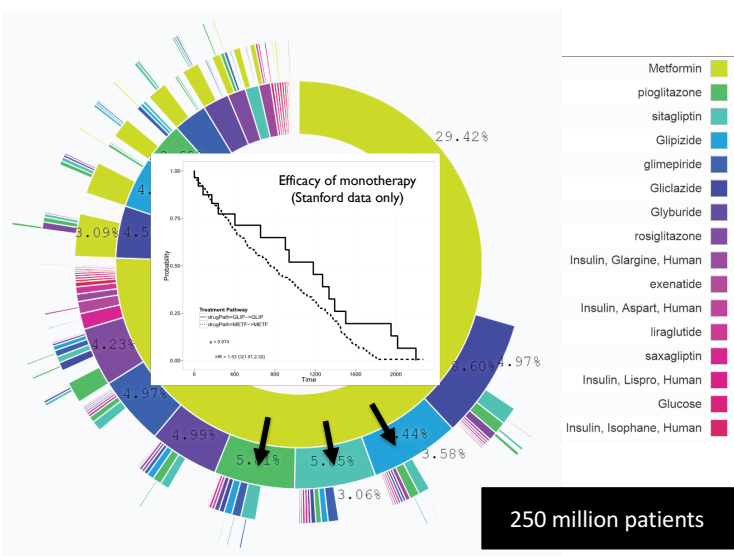
100

http://tinyurl.com/inf-consult

Example – 1: Choosing diabetes drugs

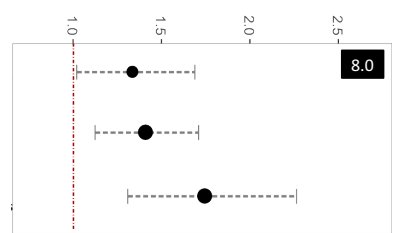


Scenario: Which second line drug to use for treating diabetics who have high HbA1c one to two months after first line treatment?



Effective treatment pathways

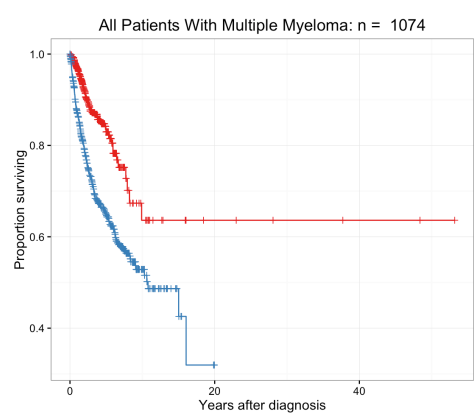
Metformin → Glipizide vs. Pioglitazone
Metformin → Sitagliptin vs. Glipizide
Metformin → Sitagliptin vs. Pioglitazone



Example – 2: Choosing chemotherapy

Example – 2: Personalized estimate

Scenario: For 55-60 year old white male patient with newly diagnosed plasma cell leukemia (PCL), what is the difference in overall survival between patients treated with intensive versus less intensive chemotherapy?



Outline of an informatics consult

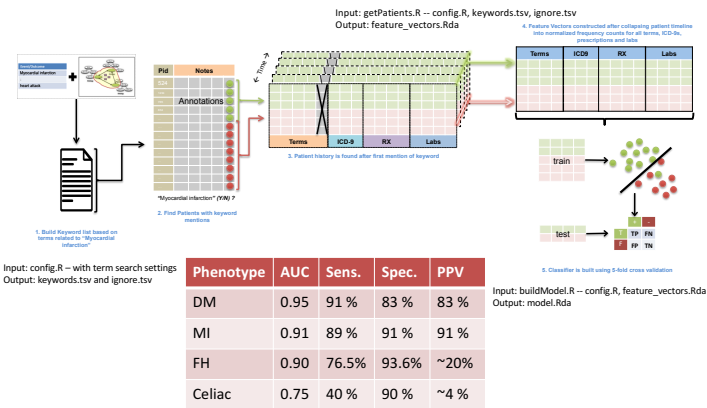
Descriptive summary

- What happened after treatment?

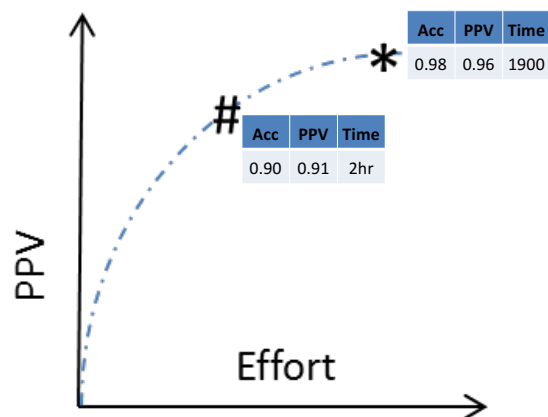
Making recommendations

- What treatment choices are typically made, given prior medical history? What are typical outcomes?
- Estimation: What is the effect of treatment choice X on outcome Y?

XPRESS- Extraction of Phenotypes from clinical Records using Silver Standards

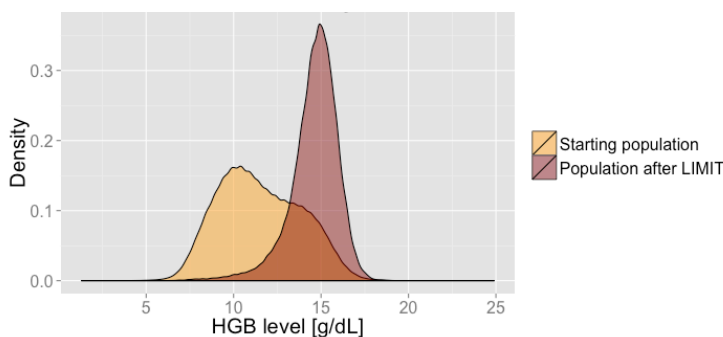


Phenotyping - effort precision trade off

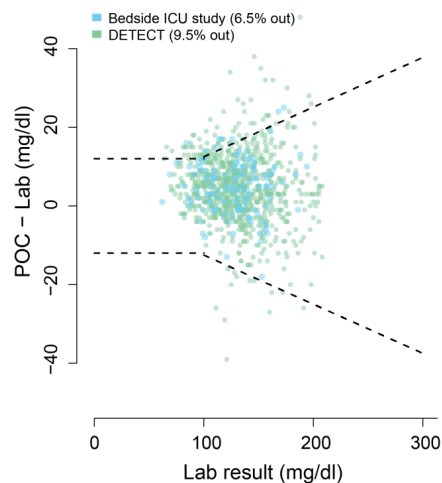


Insights

Learning true ranges of lab tests

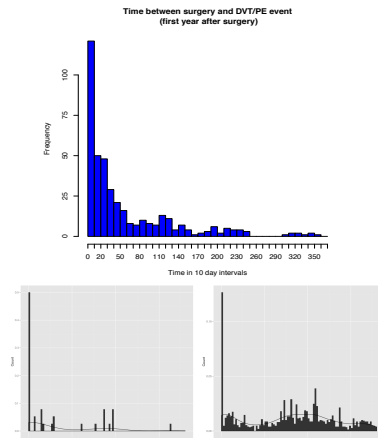


DETECT: Data mining EMRs To Evaluate Coincident Testing



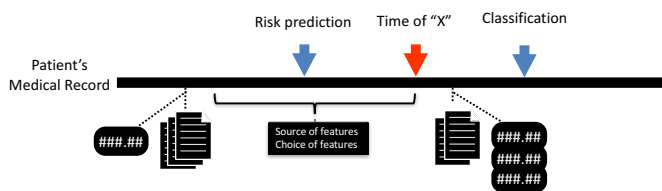
Quality metrics

- Post surgery DVT rates
- Urinary Incontinence after prostate cancer surgery

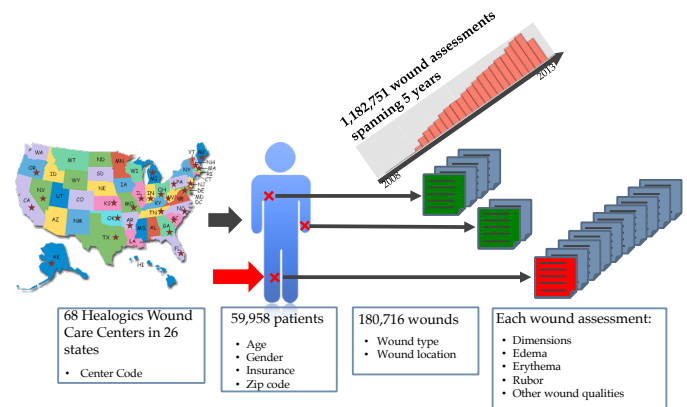


Predictive Modeling

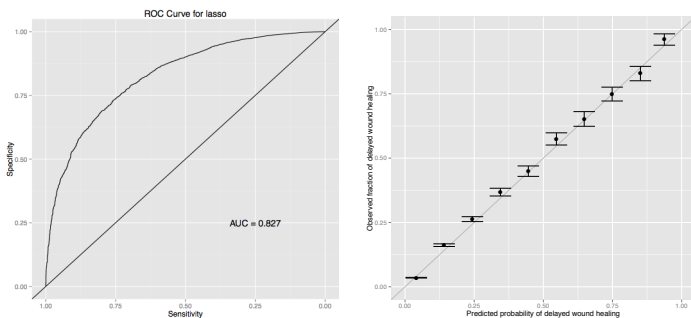
Classification or Prediction?



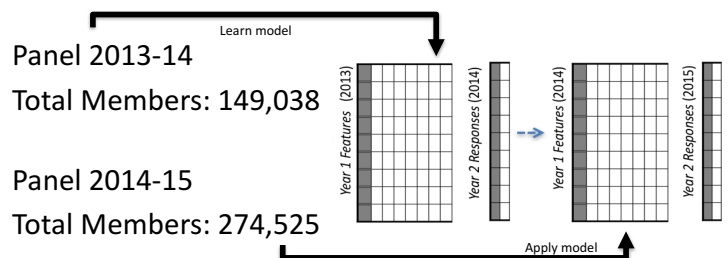
Predicting delayed healing wounds



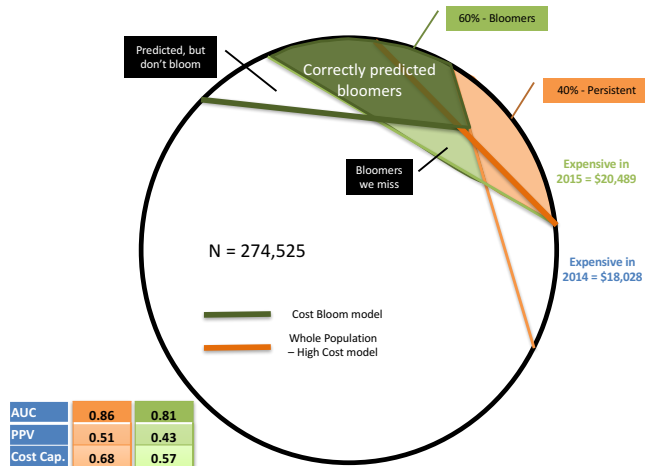
Clinically usable performance



Predicting Cost Blooms



Predicting Cost Blooms



Fruitful areas of activity

- Risk stratification: cost, latent disease, decompensation
- Personalizing evidence: risk for me, what treatment will work
- Insights into disease progression
- Using passively collected data: sensors, feature engineering
- Practice management: predicting missed appointments, medication adherence ...

Open research problems

- Data nonstationarity
- Local vs. Global models
- Handling unstructured data (text, images, time traces)
- Outcome ascertainment (and censoring)
- Evaluation: Beyond discrimination
 - calibration, net-reclassification
- Bridging the “last mile”

Acknowledgements

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- **Engineer:** Vladimir Polony
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- **Med Students:** Greg Gaskin, Jassi Pannu

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