

Predicting, and preventing cost-blooms

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SCHOOL OF MEDICINE

Healthcare in the United States

- What is the system for?
- Who are the key players, what are their roles, and what are their interests?
- How does the system function economically?
- What are the trends, failures, and opportunities?
- How, where and why, are data produced?

Government

Insurance

Hospital/
Clinic/
Doctor

Pharma/Biotech
Medical Devices
Diagnostics

Drug Store

Individual
(Patient/
Consumer)

Internet/
Library/
Journals

Vendors
Software/Web
Portals
Instrumentation
/Hardware
CROS

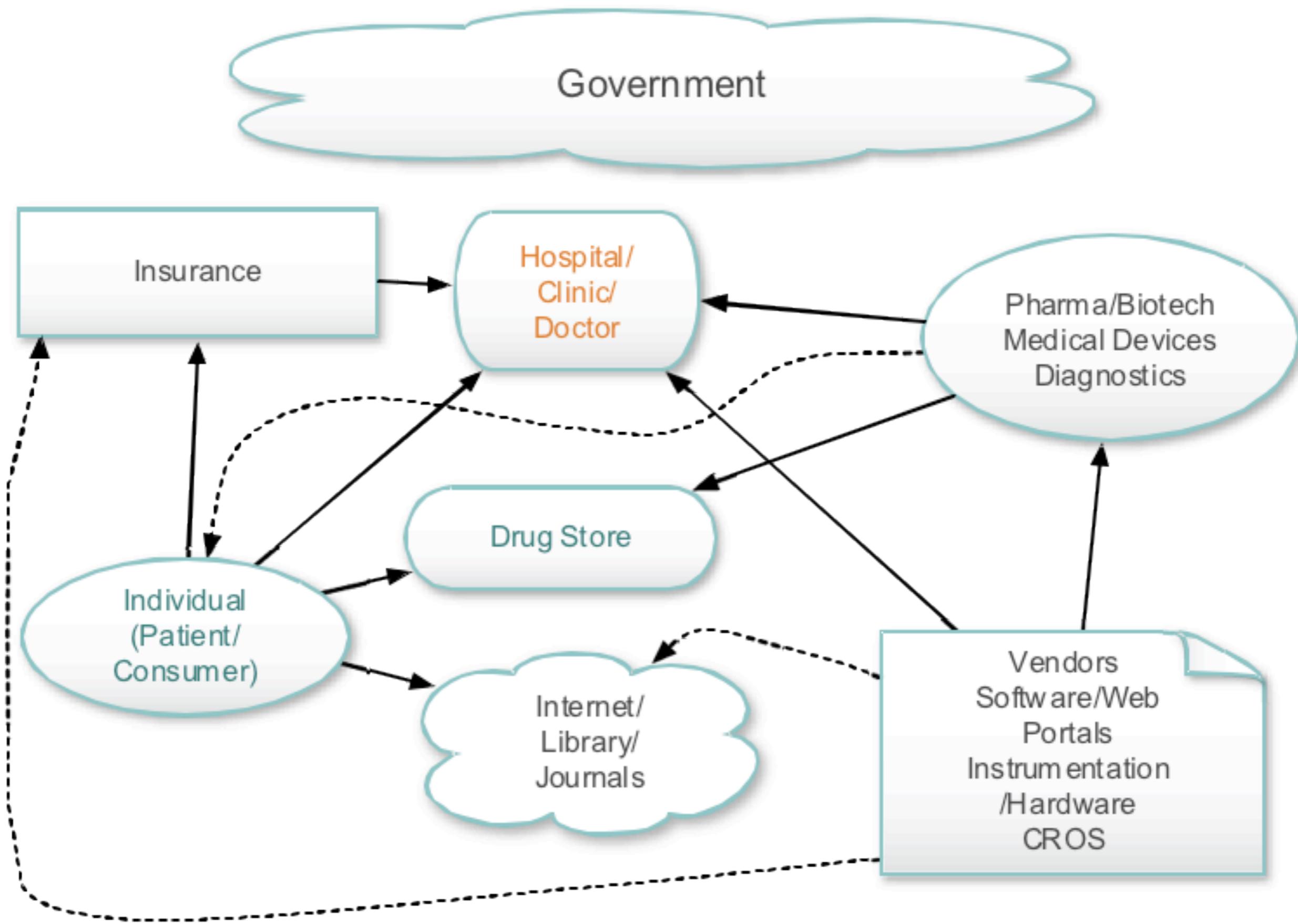


Table 2. Number of US Facilities in Health Care Sectors, 2000-2010

| Subsector | No. of Facilities in Health Care Sectors | | |
|-------------------------------------|--|----------------|---|
| | 2000 | 2010 | Annual Growth Rate, 2000-2010, % ^a |
| Offices of physicians | 195 655 | 223 797 | 1.4 |
| Social assistance | 129 053 | 158 764 | 2.1 |
| Offices of dentists | 116 494 | 129 830 | 1.1 |
| Nursing and residential care | 63 005 | 79 047 | 2.3 |
| Pharmacies and drug stores | 40 614 | 41 672 | 0.3 |
| Home health care services | 16 092 | 27 314 | 5.4 |
| Outpatient care centers | 19 700 | 27 202 | 3.3 |
| Medical and diagnostic laboratories | 9750 | 13 220 | 3.1 |
| General hospitals ^b | 6588 | 5836 | -1.2 |
| Urgent care centers | 2503 | 5419 | 8.0 |
| Retail clinics ^c | 3 | 1200 | 82.1 |
| Specialty hospitals | 499 | 956 | 6.7 |
| All others | 165 773 | 221 615 | 2.9 |
| Total | 765 729 | 935 872 | 2.0 |

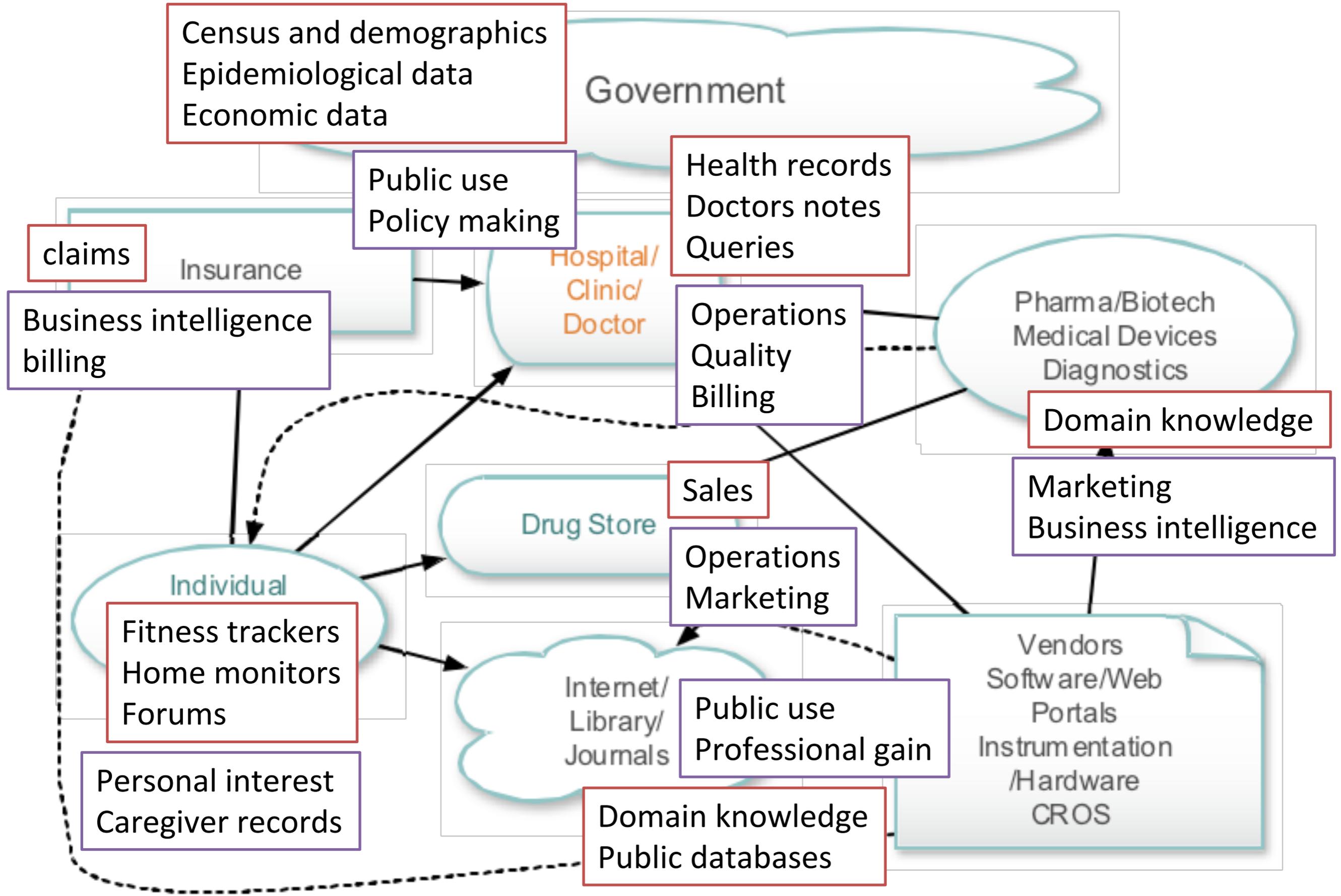
Anatomy of the US Healthcare System

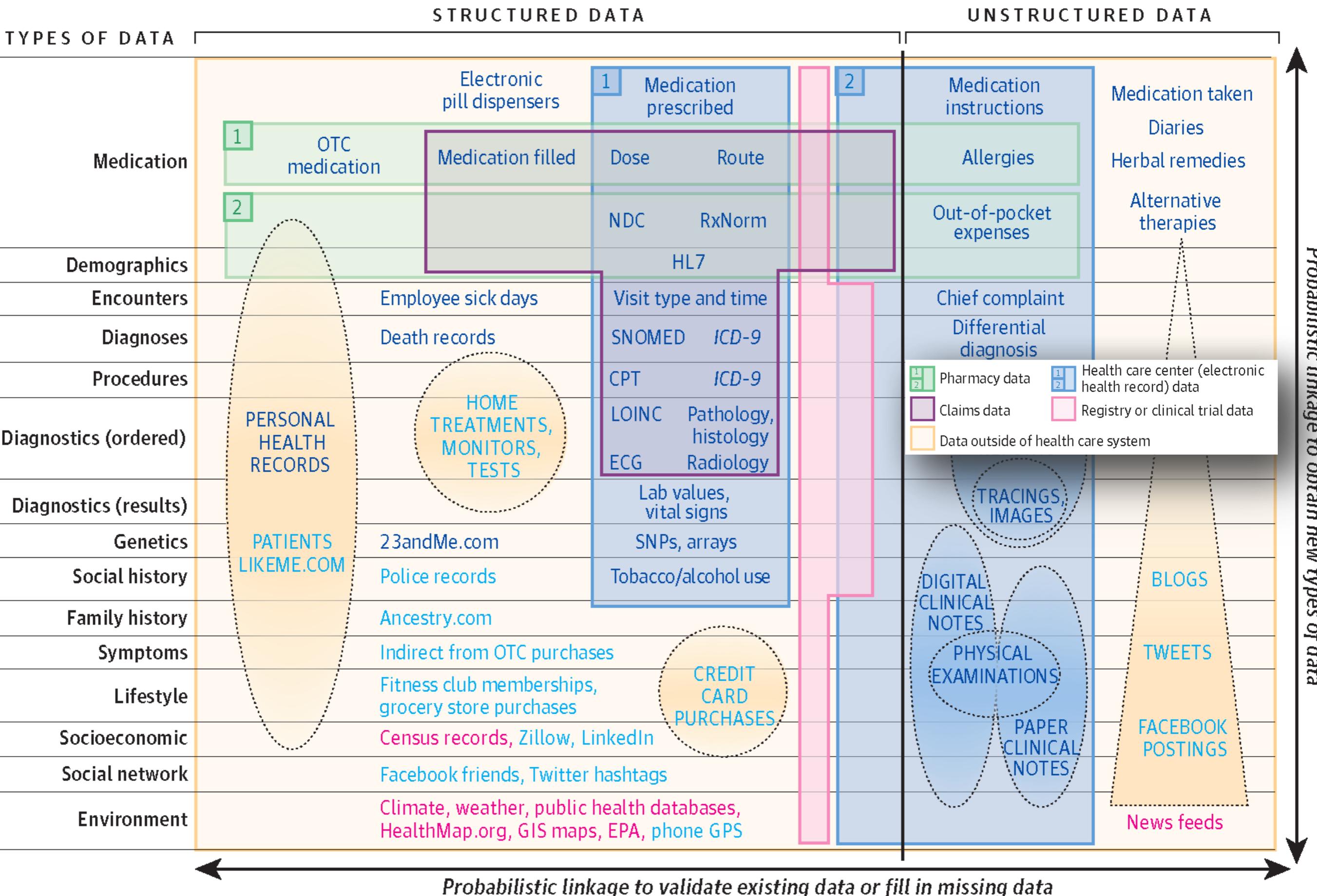
Take a minute to think, then work with your neighbor to answer the following question on your concept map:

What are the kinds of data that each of these entities generate? For what purpose?

Example: individual patients generate fitness tracker data for their own personal interest

Where and why are the data generated?





Probabilistic linkage to validate existing data or fill in missing data

Probabilistic linkage to obtain new types of data

Weber et al, JAMA 2014

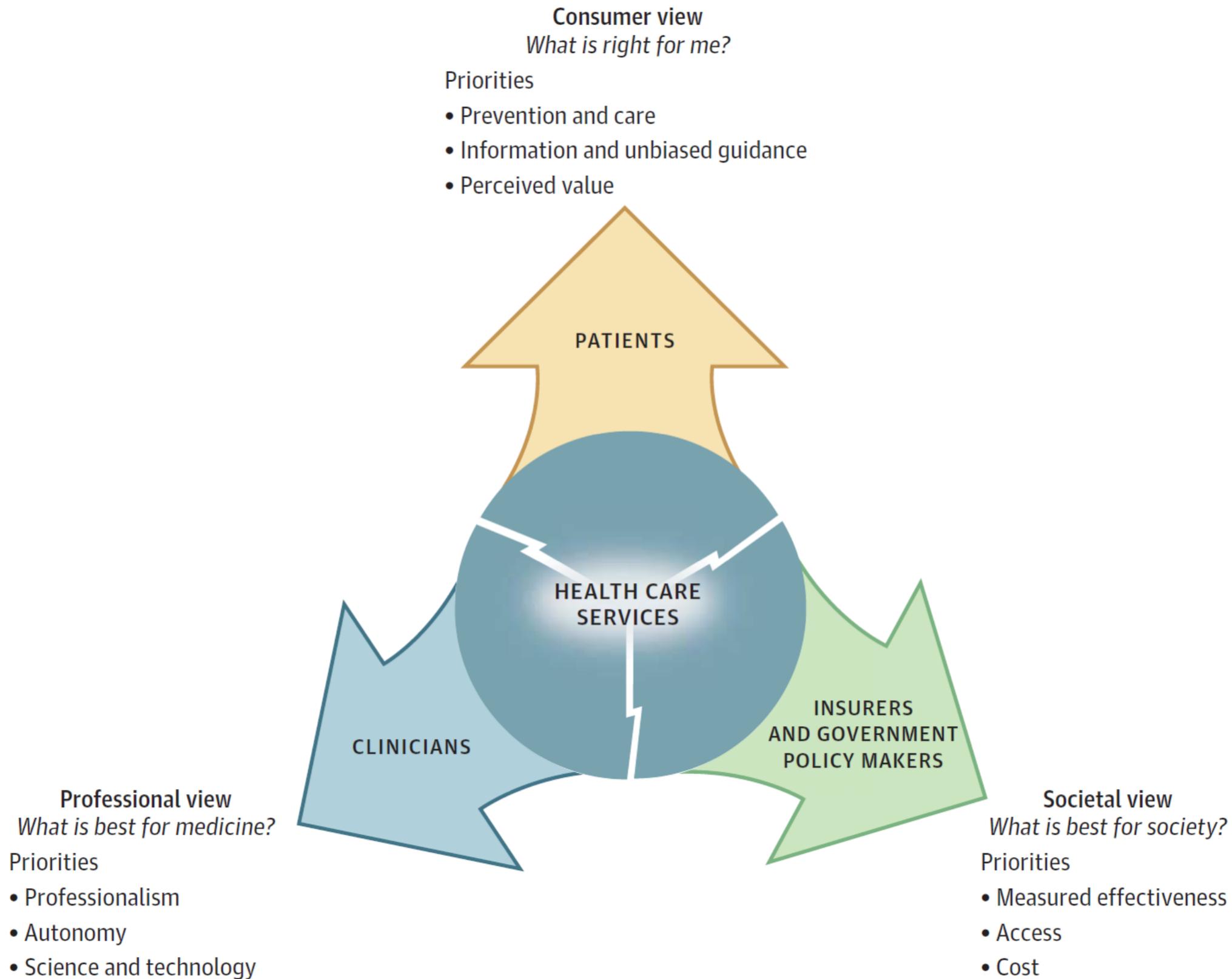
The Anatomy of Health Care in the United States

Hamilton Moses III, MD; David H. M. Matheson, MBA, JD; E. Ray Dorsey, MD, MBA; Benjamin P. George, MPH; David Sadoff, BA; Satoshi Yoshimura, PhD

- Publicly available data from 1980 to 2011, on the source and use of funds.
- In 2011, US health care employed 15.7% of the workforce, with expenditures of \$2.7 trillion, and being 17.9% of GDP.
- Three factors have produced the most change:
 - consolidation, producing financial concentration
 - information technology, in which investment has occurred but value is elusive;
 - patient empowerment, whereby influence is sought outside traditional channels.

Follow the money ... it will lead you to the problems that really need to be solved

Conflicting interests



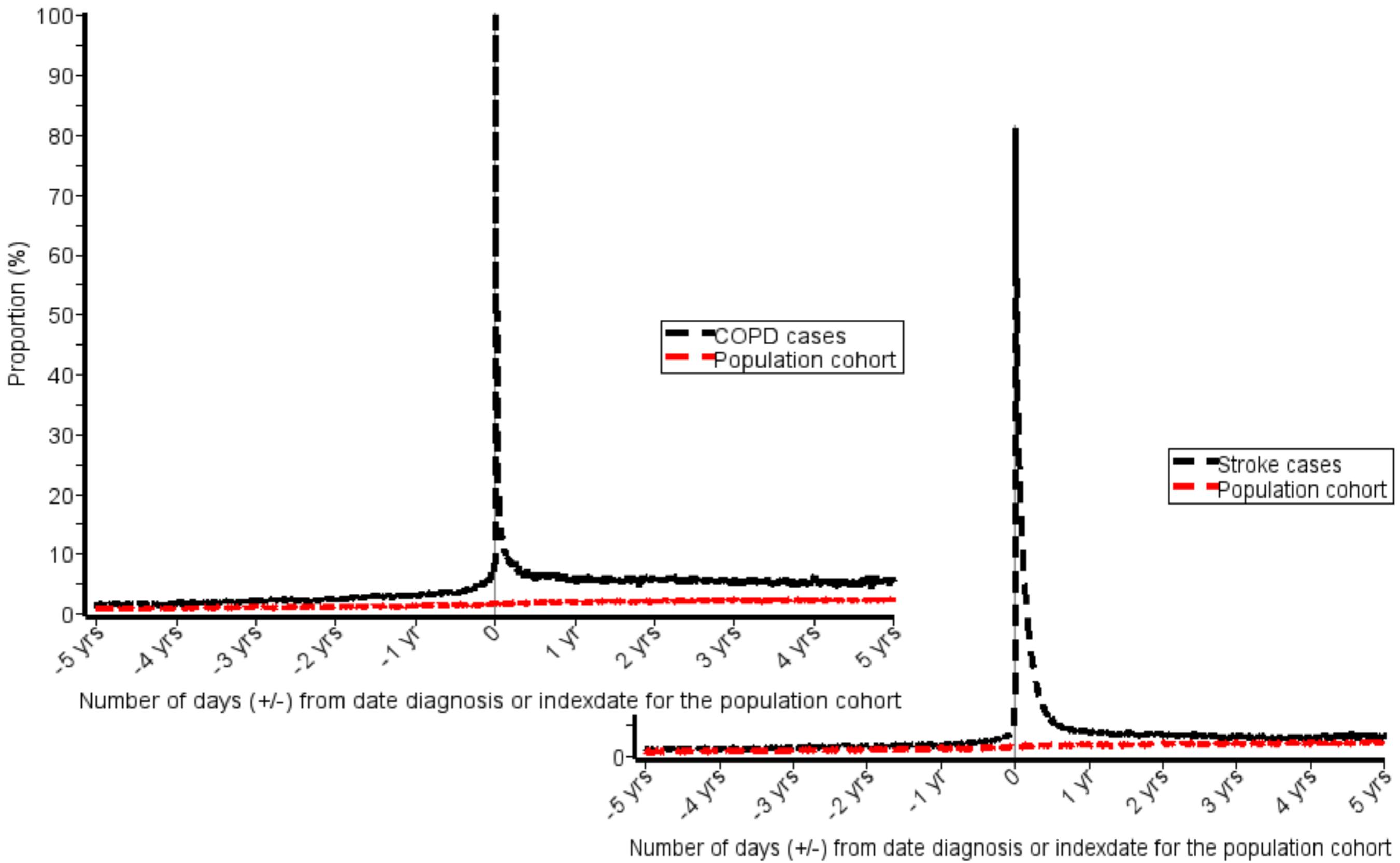
When you use these data:

- Know that priorities are different for each stakeholder, which affects the data that are generated.
- Design studies to leverage strengths and protect from weaknesses of the data. Using multiple sources is beneficial.
- Think about who is interested in the results. Targeting studies to the intersections of two or more interests is impactful.

Why predict cost?

- For “risk-adjustment”
 - Risk assessment → measuring the expected healthcare costs of individuals enrolled in a plan.
 - Risk adjustment → moving funds from plans that have less than their fair-share of high-risk enrollees to plans that have more high-risk enrollees.
- For “risk-contracting”
 - In a fee for performance model, where the provider is assuming total risk for caring for an individual, they need to know their risk exposure.
- For deciding which insurance to buy
 - As an individual, knowing your true risk allows you to buy the appropriate plan with adequate coverage.
 - E.g. should you enroll in a high deductible plan or not?

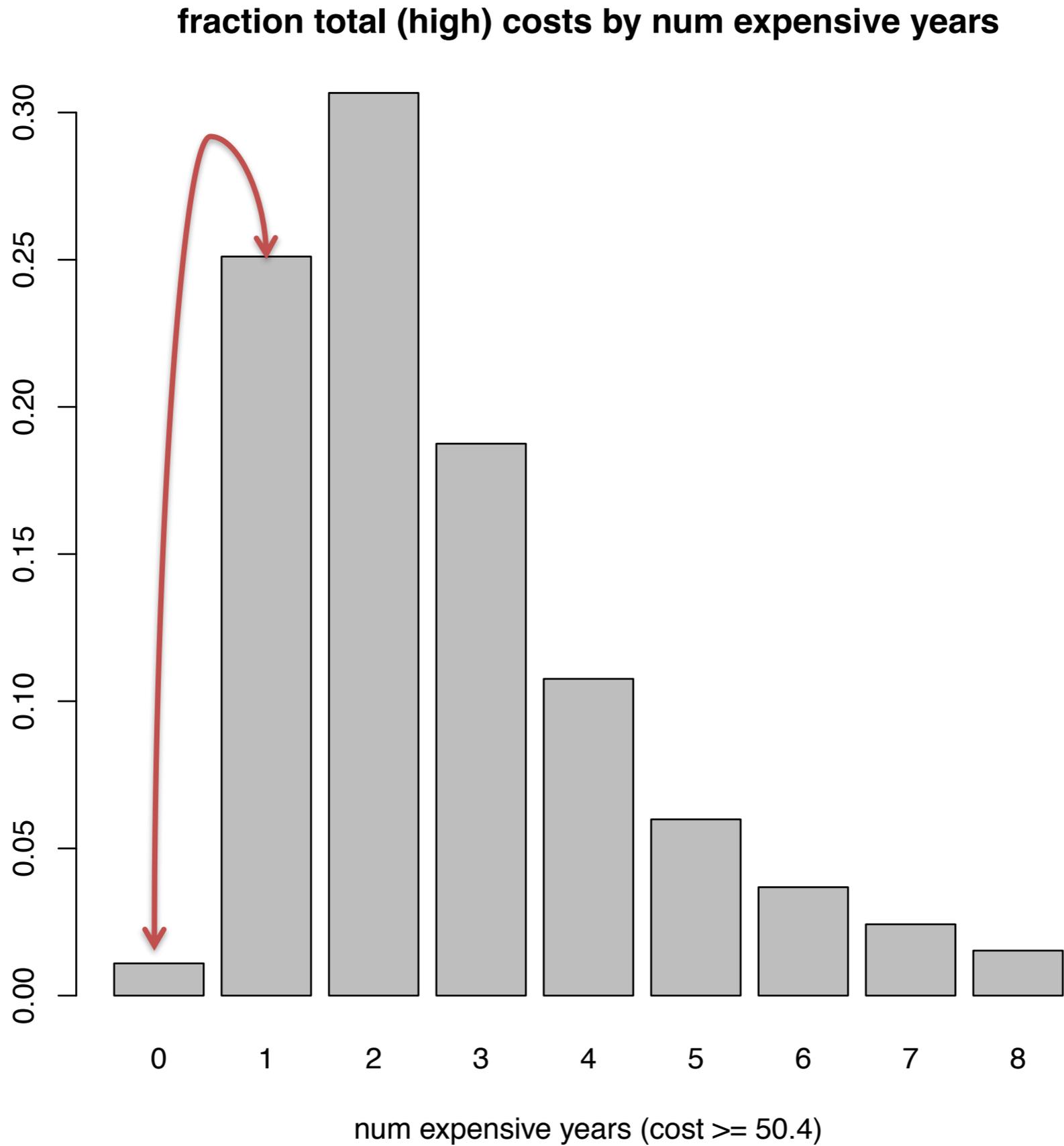
Cost at the population level



What is worth predicting?

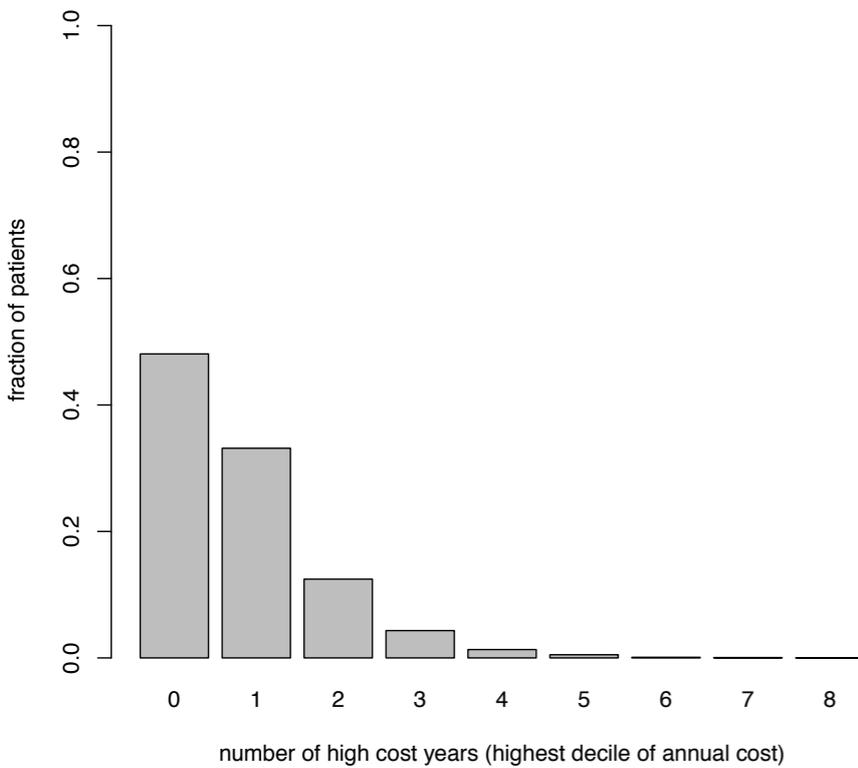
- If you have a high cost year, what is the probability that the next year is high cost?
 - 0.26 overall
 - 0.37 in high cost population
 - 0.03 in low cost population → If they become high-cost, it's an unexpected event
- High Cost vs. a Cost bloom

Anatomy of “high cost”

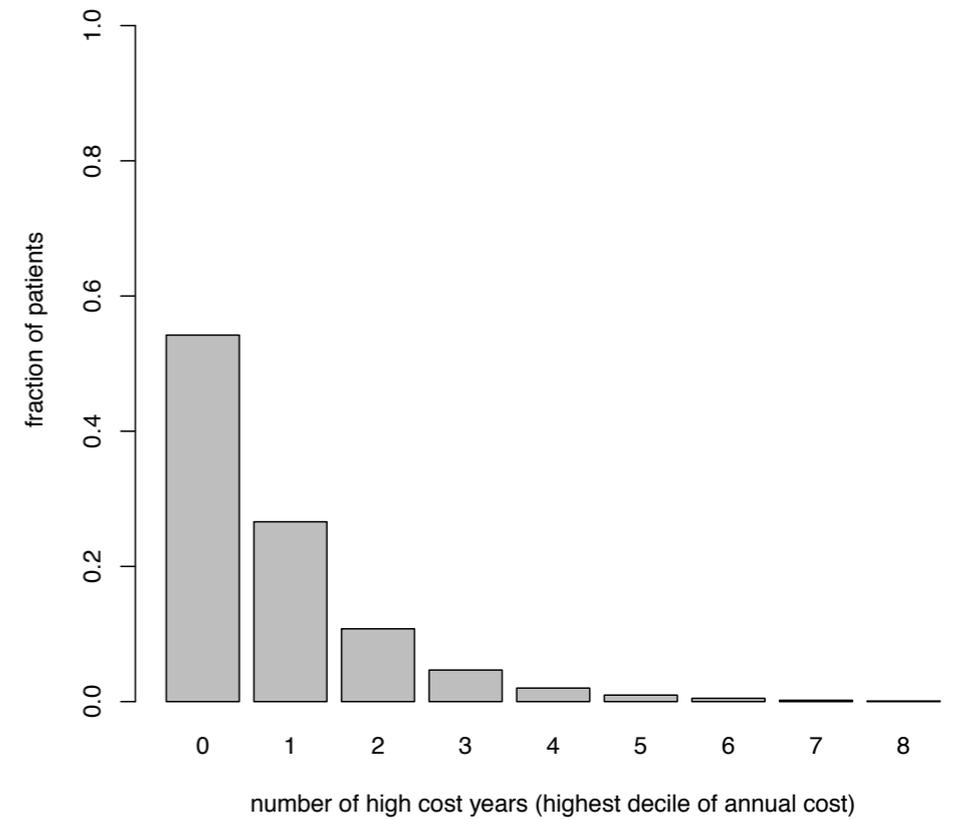


Anatomy of “high cost”

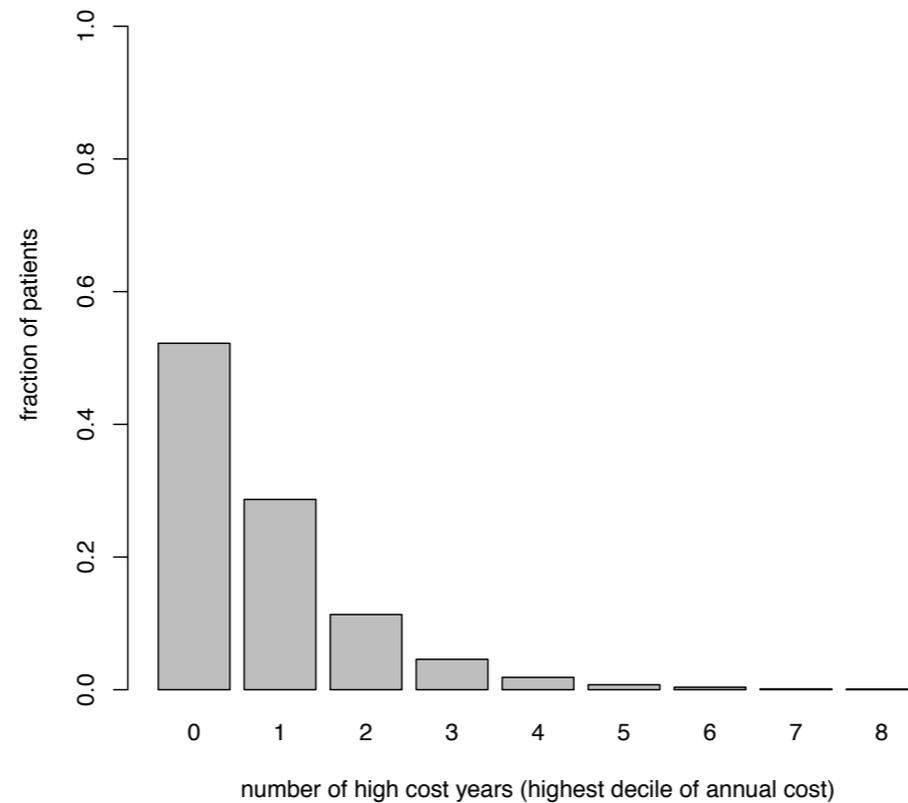
fraction patients vs number high cost years in CHF



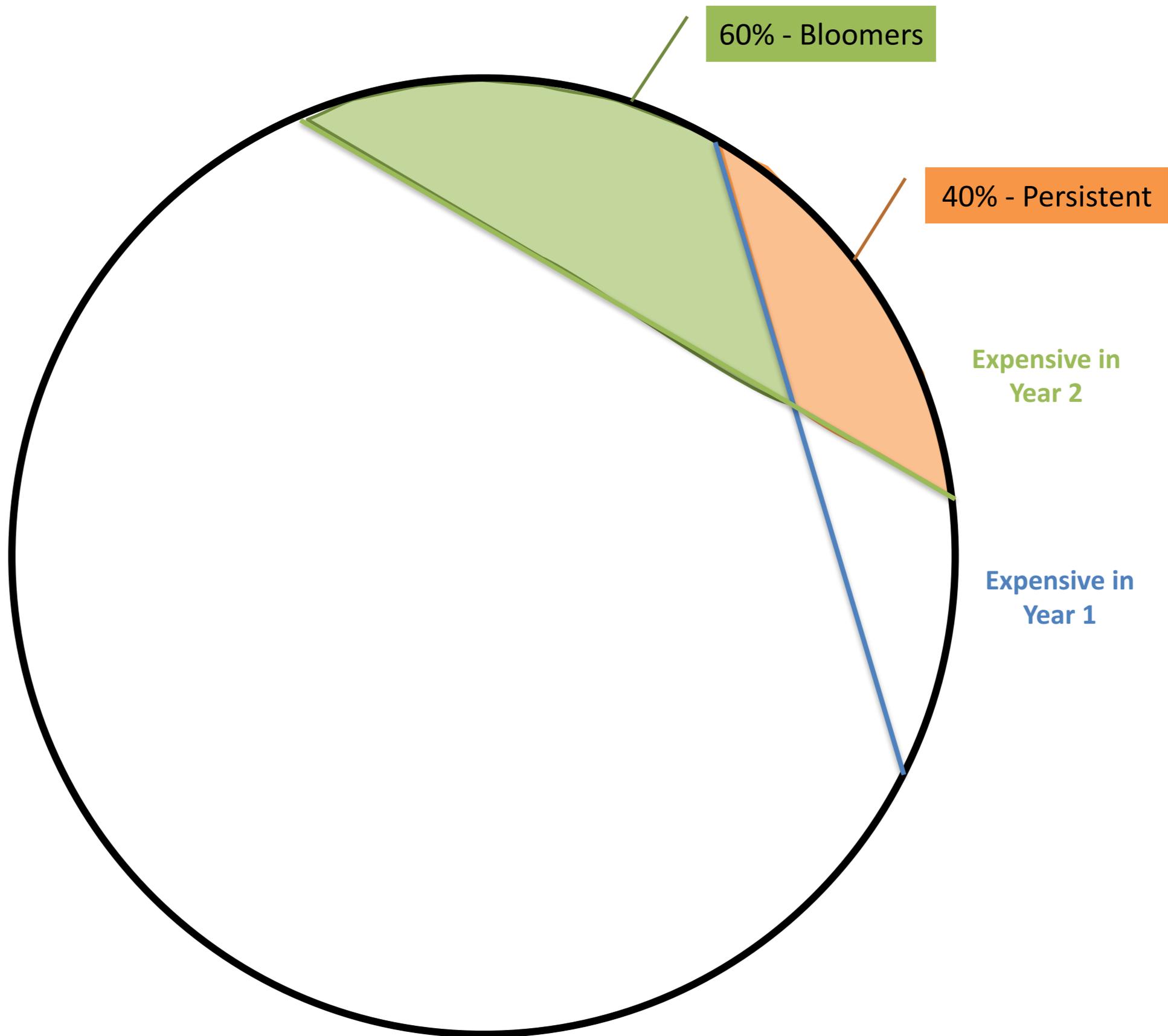
fraction patients vs number high cost years in DM



fraction patients vs number high cost years in COPD



Anatomy of the cost



Predicting cost vs. cost bloom

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Inpatient and Outpatient: Alladmissions2012_id.csv (18,717,849)
C_PATTYPE,D_INDDTO,D_UDDTO,C_ADIAG,C_DIAG,C_DIAGTYPE,D_AMBDTO,id,price
2,20JUN2003,05SEP2003, DN433, DN433, A, 20JUN2003, 1,
2,20JUN2003,20JUN2003, DN433, DN433, A, 20JUN2003, 1,
2,20JUN2003,05SEP2003, DN433, DN433, A, 05SEP2003, 1,

Prescription Registry: Prescription2012_id.csv (1,537,866)
varenr,atc_kode,expdato,varemgd,DDD,id,price
5,N05AX08,09JAN2003,1,2,553,123.53
5,N05AX08,04SEP2003,1,2,553,123.53
5,N05AX08,10SEP2003,2,2,553,247.06

Primary Care: Service2012_1_id.csv (128,737,562)
Specialekode,Ydelseskode,Tidspunktkode,Behandlingsdato,id,format,overens,price
80,8215,1,17JAN2003,1,1,181.47
80,101,1,30MAY2003,1,1,105.57
21,101,1,24OCT2003,1,2,184.58

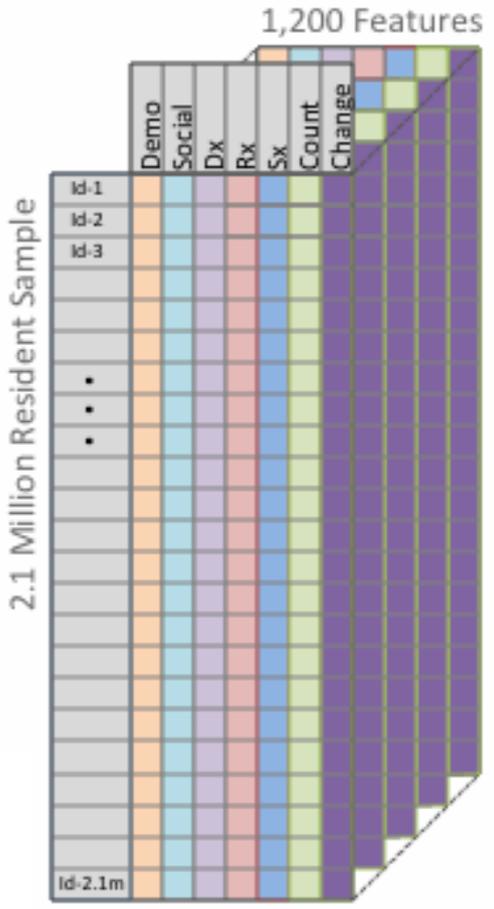
Surgery: K2012_id.csv (3,480,812)
D_INDDTO,D_UDDTO,C_ADIAG,C_OPRART,D_ODTO,C_OPR,V_OTIME,id
20JUN2003,05SEP2003, DN433, D, 05SEP2003, KJAB00, 8, 1
20JUN2003,05SEP2003, DN433, V, 05SEP2003, KKFD20, 8, 1
23AUG2006,23AUG2006, DS032, V, 23AUG2006, KEAB00, 18, 3

Demographics: pop2012_id.csv (2,146,802)
StartDato,slutdato,cpr,status,statusdato,birth,statsborger,sex,amt,birthyear,id
01JAN2003,01JAN2012,0101005003,01,01JAN2012,01JAN2000,5100,1,4,2000,1
01JAN2003,01JAN2012,0101005011,01,01JAN2012,01JAN2000,5100,1,2,2000,2
01JAN2003,01JAN2012,0101005038,01,01JAN2012,01JAN2000,5100,0,2,2000,3

Social Relationships: Familystatus2012_id.csv (3,175,731)
C_CIVSTD,d_start,d_slut,statusdato,id
M,01FEB1945,01JAN2012,1
W,28JAN2009,01JAN2012,1
U,.,JAN2012,2
    
```



| | | |
|------------------------------------|--|------------------------------|
| Demographics & Social Relationship | POP (Demo) | |
| | Age Gender | Land Resident Status |
| | Individual-level Social Relationships (Social) | |
| Clinical Variables | Married Unmarried Divorced | Widowed ... |
| | Hospital (Dx) | Specialist (Dx) |
| | ICD10 -> CCS ICD10 -> CCI | ICD10 -> CCS ICD10 -> CCI |
| | Medications (Rx) | |
| | ATC (4 th Level) | |
| | Surgeries (Sx) | |
| | NOMESCO Surgeries and Procedures | |
| Feature Extraction | Count | |
| | Hospital LOS Dx, Sx, Rx GP | ED Specialist ... |
| | Change Δ | |
| | Family Status Change Temporal change in count variables | |

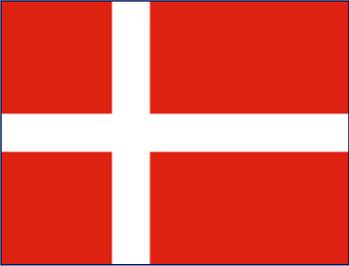


Trend Analysis 2004-2011

Comparison of Alternative Cost-prediction Models 2010-2011

Prediction Task 1:
Population-level High-Cost

Prediction Task 2:
Cost Blooms



2,146,801
Residents
2004-2011

Active Resident
2010 in

1,557,950

Prediction
Sample 1

Not
Active
in 2010

588,851

*Task 1:
Selection
Criteria*

Bottom 90% of
Population Health
Spending in 2010

1,402,155

Prediction
Sample 2

Top
10%
in
2010

155,795

*Task 2:
Selection
Criteria*

Model Features

| Residents | STANDARD FEATURES | | | | | | Clinical Registries | | | | Civil Reg. System | |
|------------------|-------------------|--------|--|-------|--|-----------|----------------------------------|------------------------------|---|---|-------------------|-------------------|
| | Age | Gender | Risk Scores | Costs | | Costs | Clinical Code Sets | Visits Counts | Recency | Social Relationship | Danish District | |
| | | | | | | | | | | | | ENHANCED FEATURES |
| PID ₁ | 45 | F | CCS disease and CCI chronic condition scores | All | Hospital and Hospital Outpatient Clinic (HO) | Drug (Rx) | Primary Care and Specialist (PC) | ICD, NOMESCO, ATC categories | Hospital, Outpatient Clinic, Primary Care, Specialist, Medication, Treatments and Surgeries | Moving Averages of Diagnoses, Costs, Visits | Married-Widowed | 1 |
| PID ₂ | 34 | F | | | | | | | | | Unmarried | 4 |
| PID ₃ | 22 | M | | | | | | | | | Unmarried | 2 |
| PID ₄ | 32 | M | | | | | | | | | Married | 2 |
| ... | ... | ... | | | | | | | | | ... | ... |
| PID _N | 71 | F | Widowed | 1 | | | | | | | | |

Responses

| Residents | High Cost | Cost Bloom |
|------------------|-----------|------------|
| PID ₁ | 0 | 0 |
| PID ₂ | 0 | 0 |
| PID ₃ | 1 | 1 |
| PID ₄ | | |
| ... | ... | ... |
| PID _N | 1 | NA |

Prediction Model Types

Models 1 & 2

Model 3

Models 4 & 5

Standard Features
Binary Logistic Regression

Enhanced Features
Binary Logistic Regression

Enhanced Features
Elastic Net Penalized Logistic Regression

Model Descriptions

Model 1: Age + Gender + CCS + CCI

Model 2: Model 1 + Hosp. Inpt & Outpt, Drug Costs

Model 3: Model 2 + Primary Care Costs

Model 4: Full Feature Set without Costs

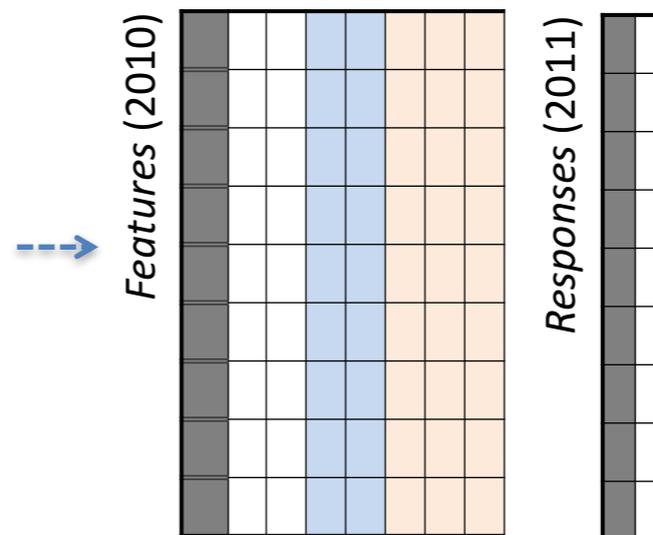
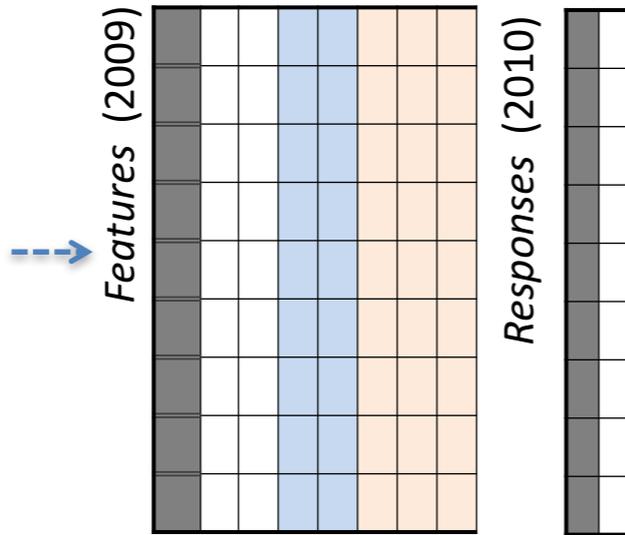
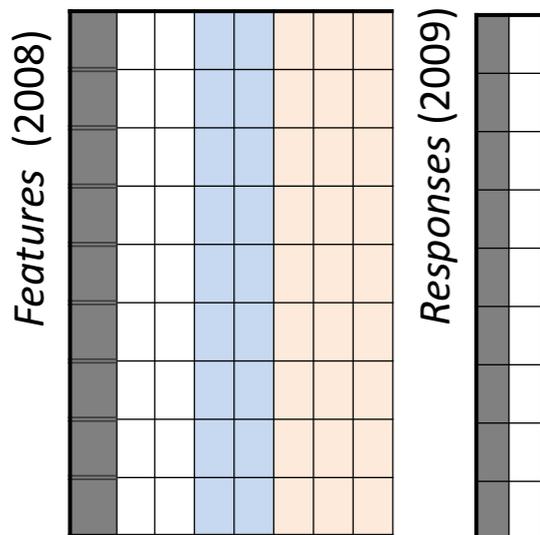
Model 5: Full Feature Set (1059 total features)

Model Development and Evaluation

Training

Tuning

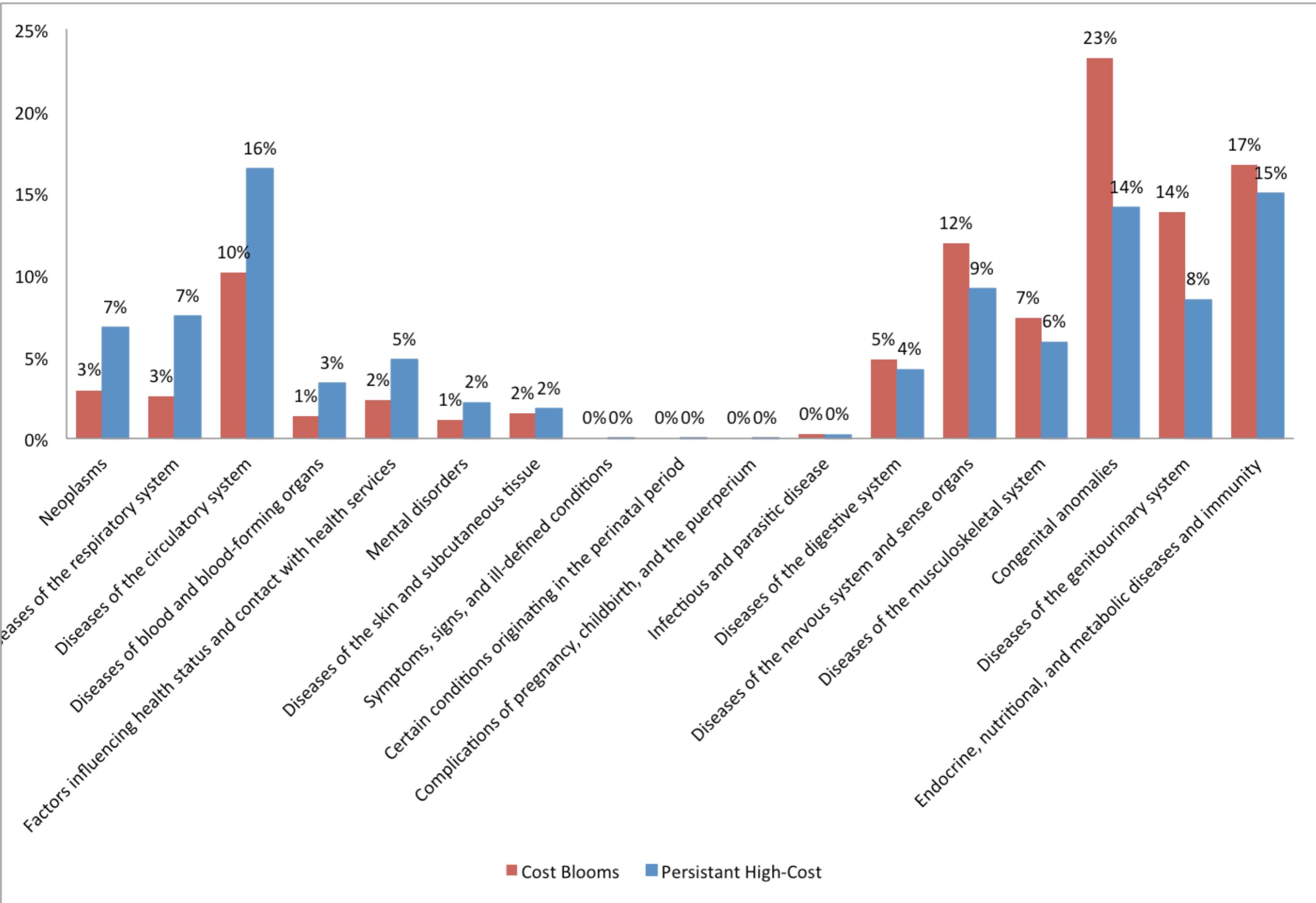
Testing



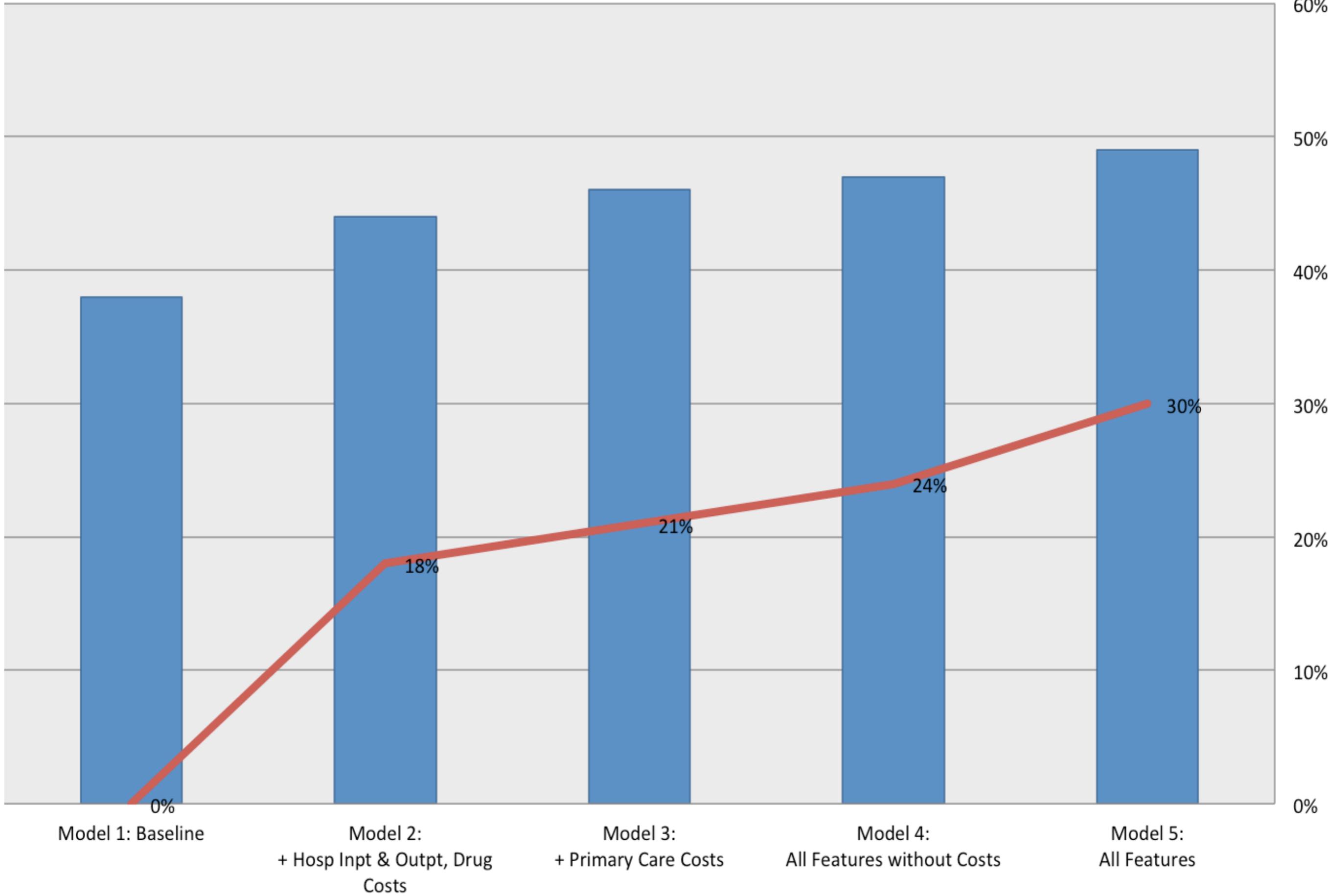
$$Cost = 100 \times \frac{\text{Cost of Predicted High-Cost Group}}{\text{Cost of Actual High-Cost Group}}$$

Results

| Prediction Task | Evaluation Metric | Model 1: Baseline |
|---|-------------------|-------------------|
| High-cost (N=1,557,950) | AUC | 0.775 |
| | Cost Capture | 0.495 |
| Cost-bloom (N=1,402,155) | AUC | 0.719 |
| | Cost Capture | 0.376 |



■ Cost Capture ■ % Increase over Baseline



Predictions and Actions

| | | | | | |
|--------------|------------|--|--------------|--------------------------|----------------------|
| Take on Risk | | | | | |
| Service | | | | | |
| Intervention | | Possible further work: <ul style="list-style-type: none">• Summarize the bloomers.• Exploratory analyses to design interventions. | | | |
| List | ✓ | | | | |
| | Cost-bloom | Mortality | Chronic Pain | Pre-diabetes to Diabetes | Risk of Opioid abuse |

Possible intervention types

- **Relationship-based Interventions:** Suggest high value interventions to attending physicians, healthcare system medical directors, and/or patients.
- **Rules-based Interventions:** Where relationships with providers are insufficiently developed, alteration of plan rules governing coverage, pre-cert, provider network inclusion, provider incentives, patient incentives, formulary tiers, and/or DUR screens.

Summary

1. Important to distinguish cost-bloomers from persistent high-cost patients.
2. 30% improvement in cost capture over a standard diagnosis-based claims model.
3. Including a patient's social relationship status, and temporal information such as the frequency and recency of healthcare events, improved prediction.
4. Predictions enables precise targeting of the subset of patients who are at the most risk of a cost bloom.
5. Example of machine learning that matters.

Tips for your predictive modeling projects

Data clean up will take about 80% of the time

- If you took a short cut here, stop.

Try simple things first

- “Deep learning” is not the right answer every time!

Ask whether:

- More data will increase performance
- More features will increase performance
- Errors from different models are correlated

Don't get fooled by AUC

- Examine precision recall, calibration, net-reclassification

Don't get attached to one model

Remember that the data are changing under you

Think about model deployment

- Ease of applying the model
- Think about the cost of taking action
- Precision @ K

Open research problems

- Handling data nonstationarity
- Local vs. Global models
- Handling unstructured data
- Outcome ascertainment (and censoring)
- Evaluation: Looking beyond discrimination (calibration, net-reclassification)
- Bridging the “last mile”

Credits

- Suzanne Tamang
- Arnold Milstein
- Alan Glaseroff
- Thomas Wang