Machine Learning for Health Economics and Outcomes Research

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Poll Question

What is your familiarity with machine learning techniques?

- Not familiar or minimal
- Read a few papers but never implemented
- Implemented in at least one analysis
- Experienced user

HEALTH ECONOMICS POLICY OUTCOMES

“ Learning two fields takes, surprisingly, twice as long as learning one. But it’s worth the investment because you get to solve real problems for the first time. ”

Barbara Engelhardt | Princeton

“ In both private enterprise and the public sector, research must be reflective of the society we’re serving. ”

Rediet Abebe | Harvard

“ …behind every data point there is a human story, there is a family, and there is suffering. ”

Nick Jewell | LSHTM & UC Berkeley

DATA

Electronic Databases

The increasing availability of electronic health information offers a **resource to health researchers**

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General usefulness of this type of data to answer targeted scientific research questions is an open question

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May need **novel statistical methods** that have desirable properties while remaining computationally feasible

EHR ≠ EHR

BILLING CLAIMS

IBM Watson Health

CMS

CLINICAL RECORDS

IMAGING

REGISTRIES

SEER

Department of Health Care Policy • Harvard Medical School
Mass-DAC
Data Analysis Center

SURVEYS

United States Census Bureau

cahps

GOVERNMENT SOURCES

WEARABLE & IMPLANTABLE TECH

fitbit

DIGITAL

Bing

Google

NEWS MEDIA

Post Register
LOCAL • PROVEN • ESSENTIAL

Moscow-Pullman Daily News

EHR ≠ EHR

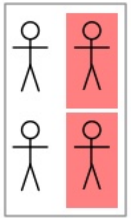
Health Affairs

Health Care Claims Data May Be Useful For COVID-19 Research Despite Significant Limitations

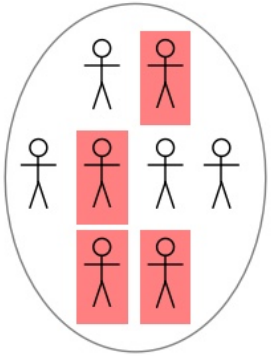
Maimuna S. Majumder, Sherri Rose

GENERALIZABILITY

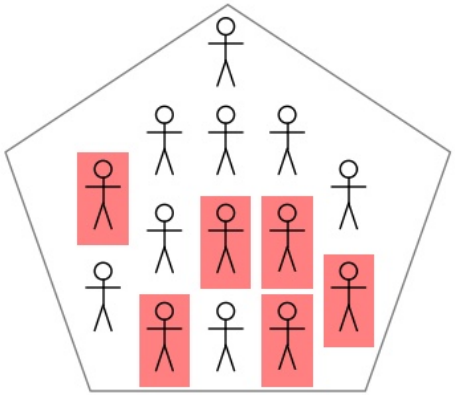
Prediction
Clustering
Inference
Generalizability



RANDOMIZED TRIAL

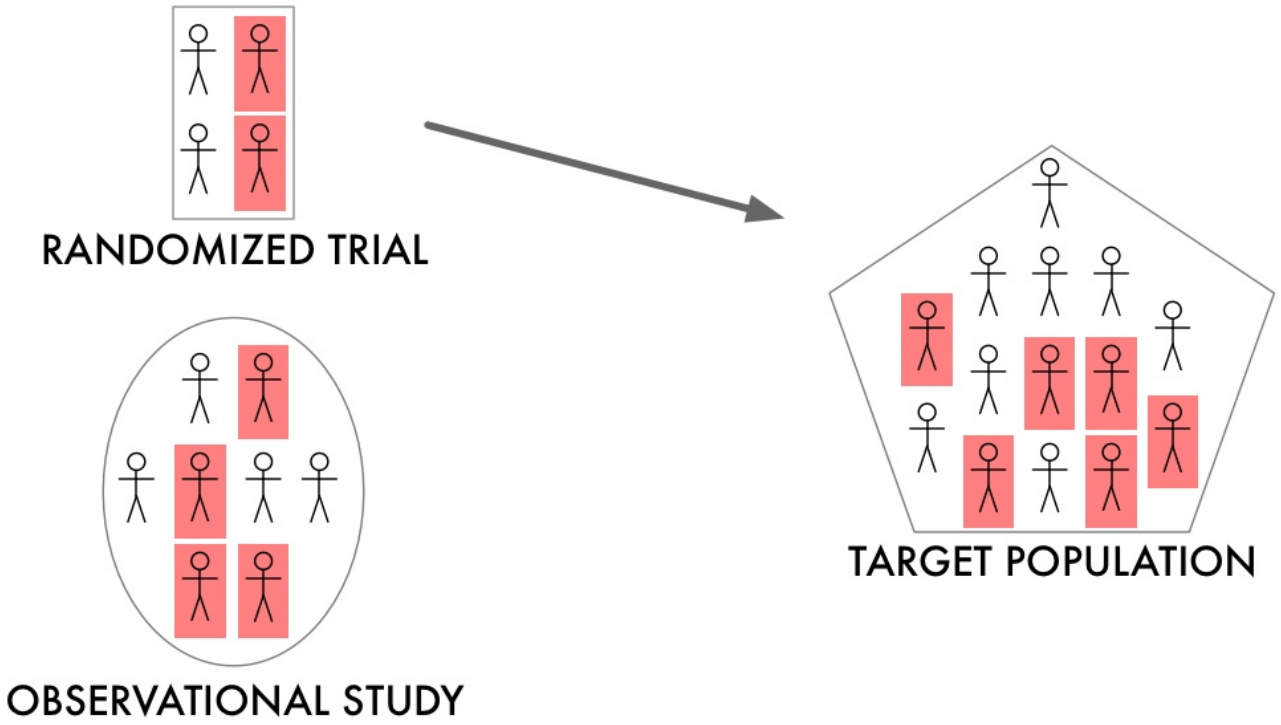


OBSERVATIONAL STUDY



TARGET POPULATION

Prediction
Clustering
Inference
Generalizability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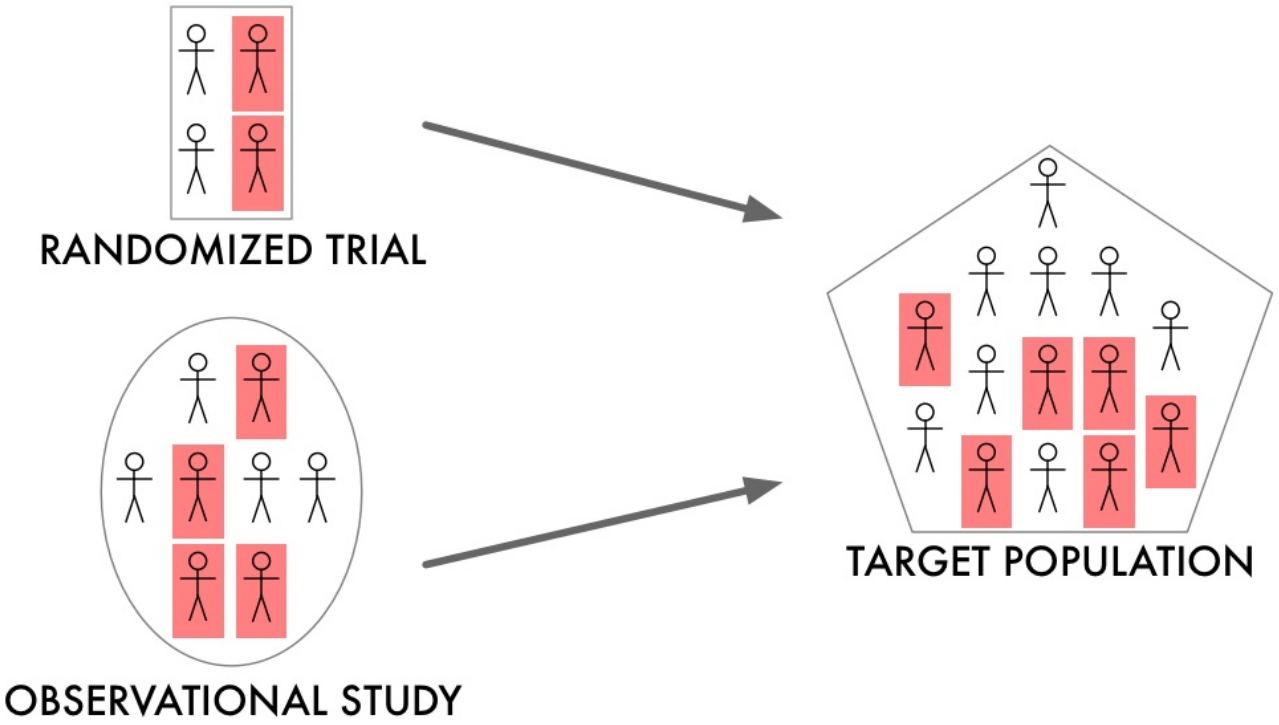
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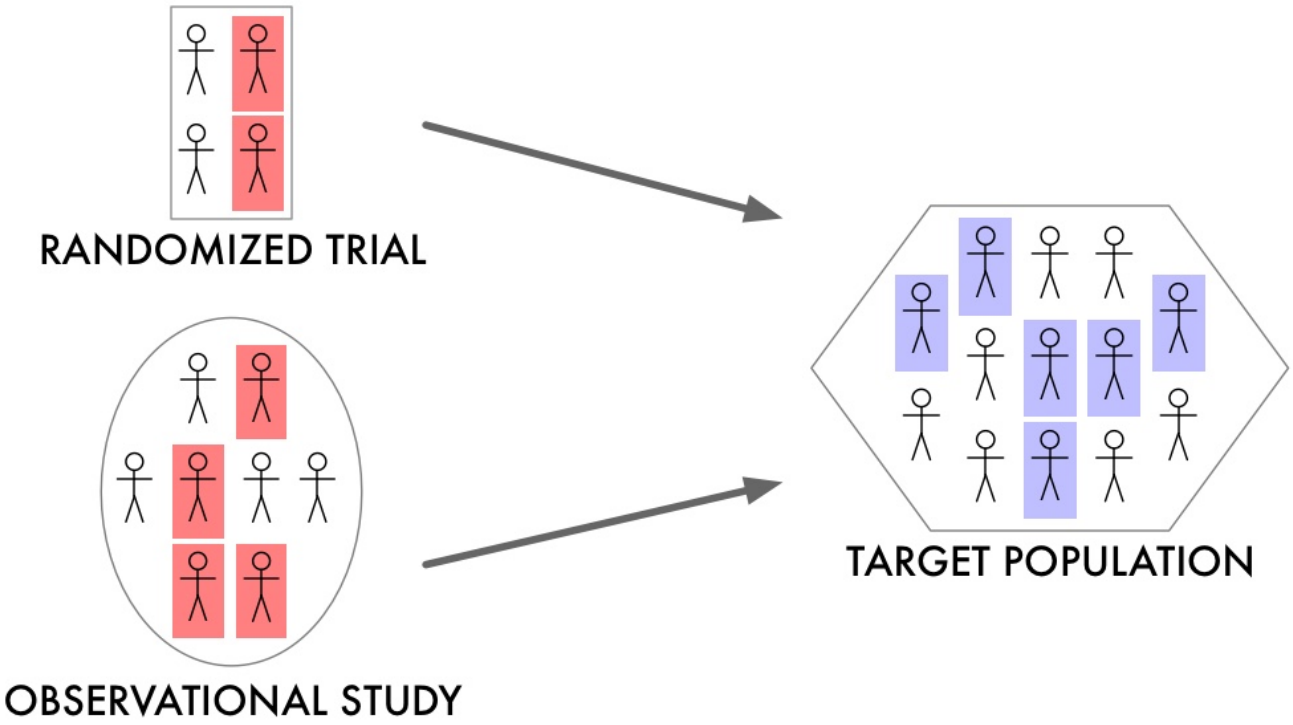
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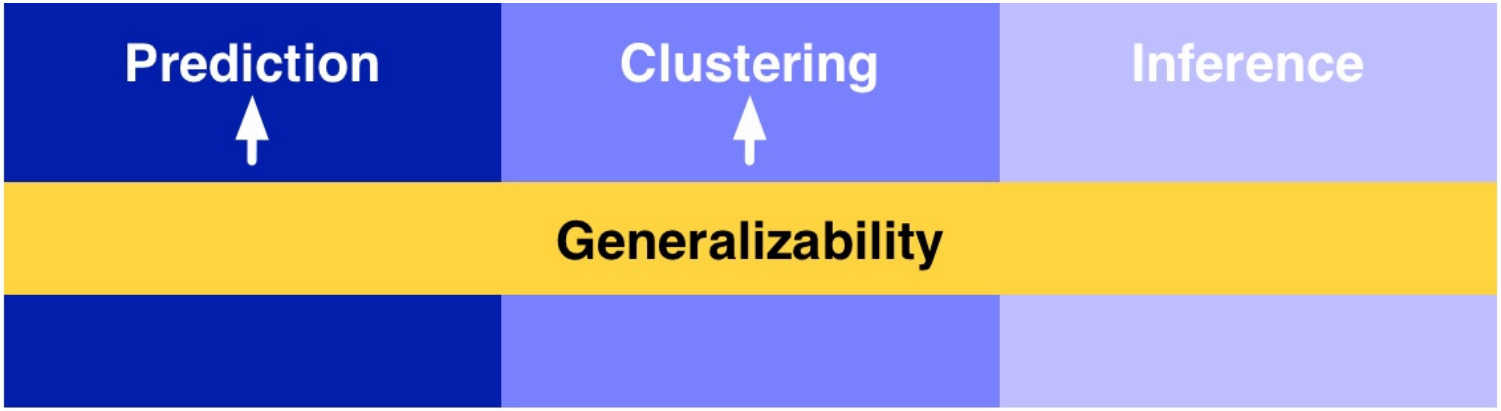
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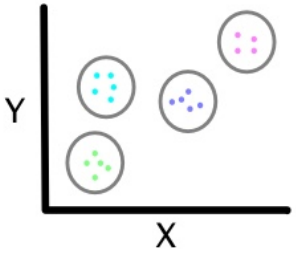
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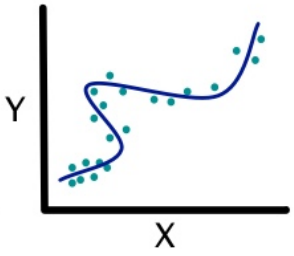
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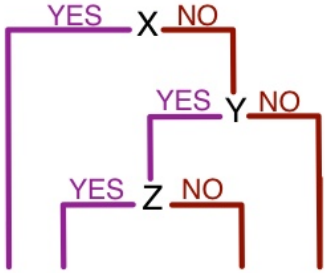
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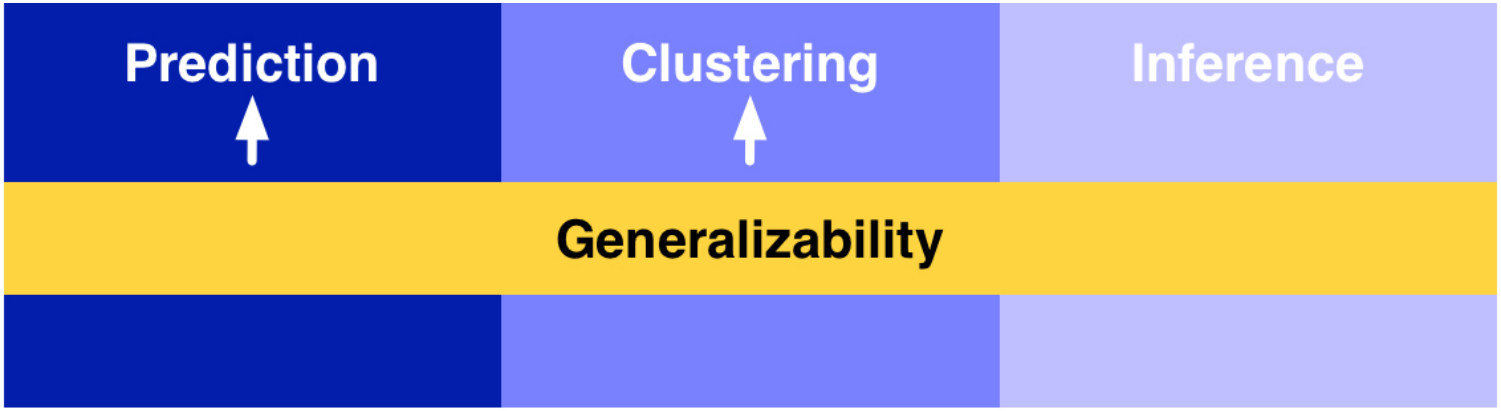
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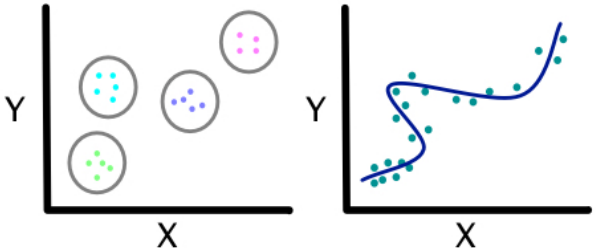
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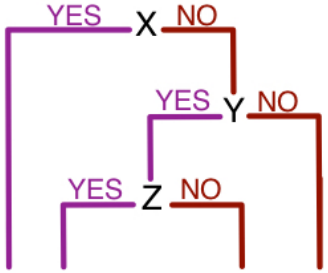
YES
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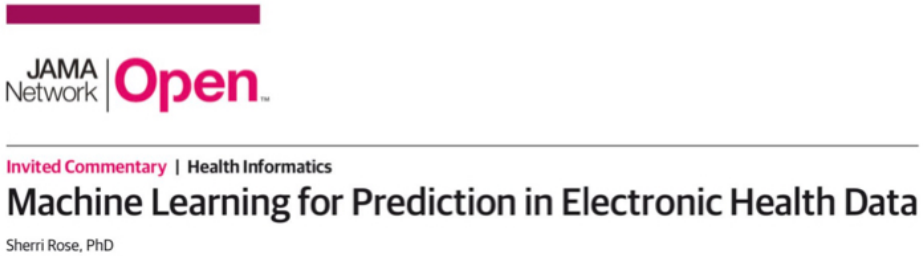
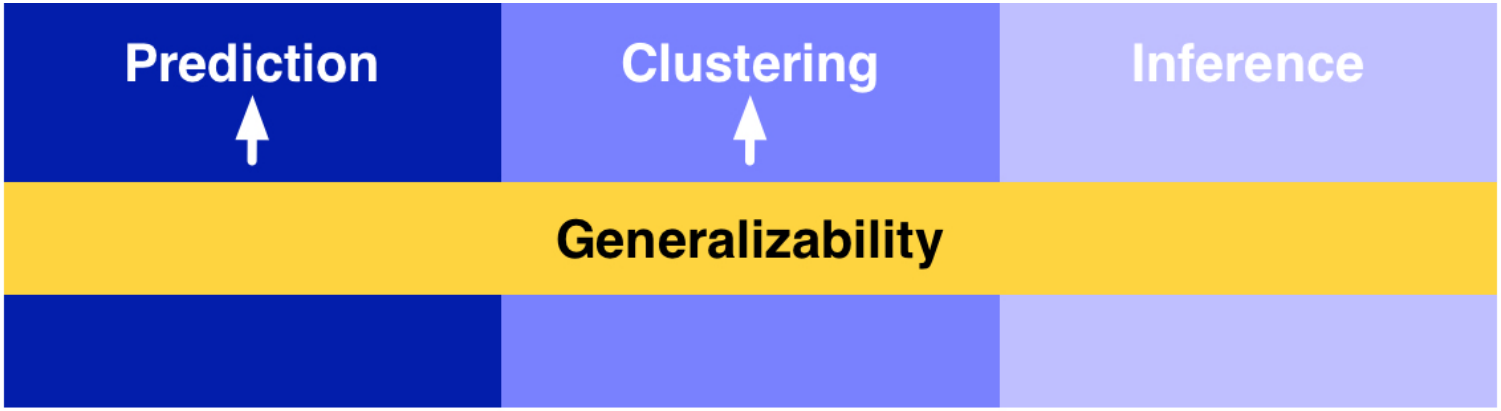
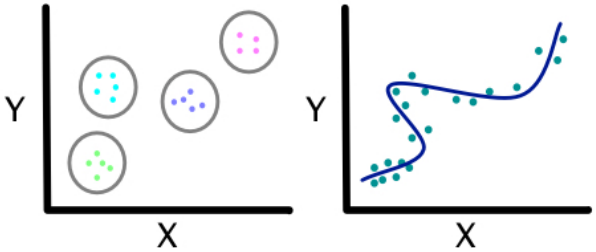
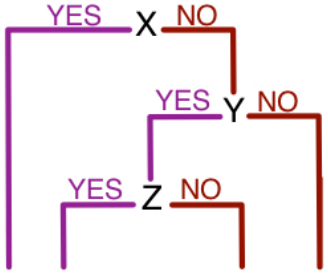

JAMA Network | Open
Invited Commentary | Health Informatics
Machine Learning for Prediction in Electronic Health Data
Sherri Rose, PhD







JAMA Network | Open

Invited Commentary | Health Informatics

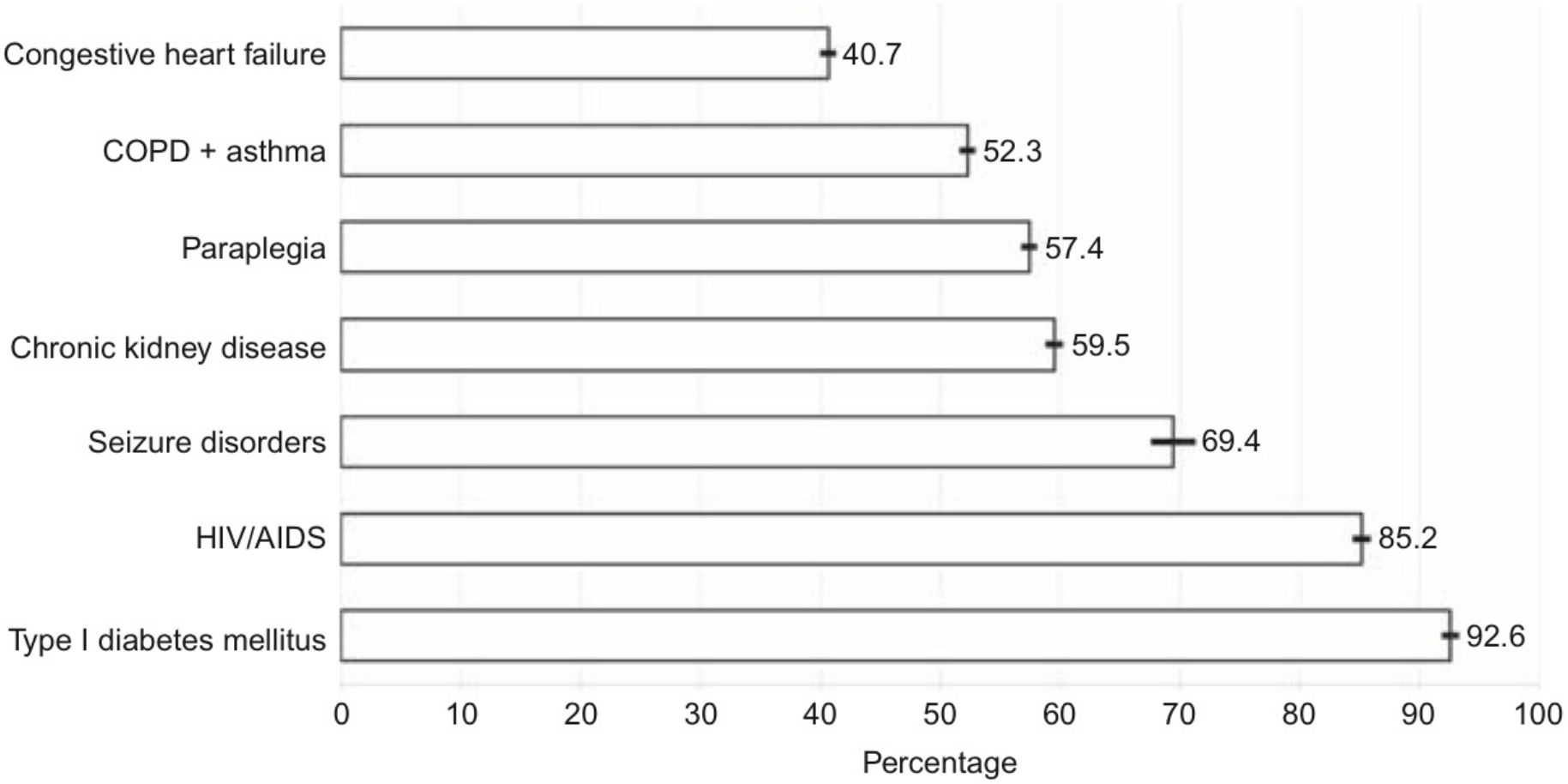
Machine Learning for Prediction in Electronic Health Data

Sherri Rose, PhD

> "The machine learning researchers who develop novel algorithms for prediction and the clinical teams interested in implementing them are frequently and unfortunately 2 nonintersecting groups."

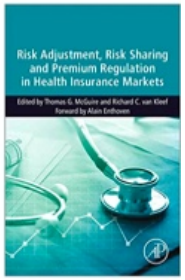
DATASET SHIFT

Chronic Conditions



Risk Adjustment for Health Plan Payment

Randall P. Ellis , Bruno Martins and Sherri Rose

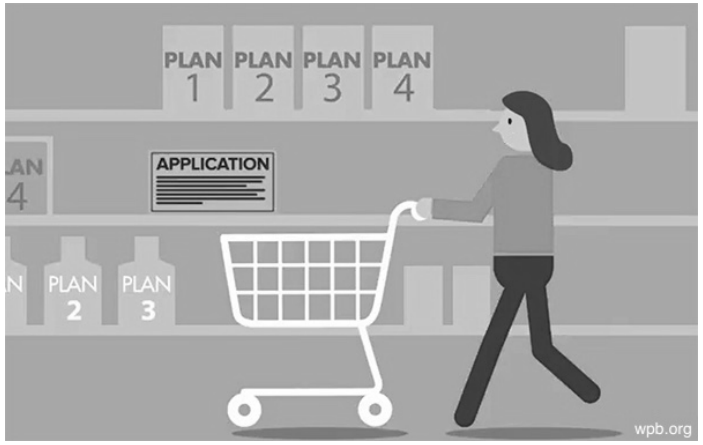


FAMILIAR QUESTIONS, DIFFERENT PROBLEMS

Plan Payment Risk Adjustment

Over 50 million people in the United States currently enrolled in an insurance program that uses risk adjustment

- Redistribute funds based on health
- Encourage competition based on efficiency and quality
- Massive financial implications



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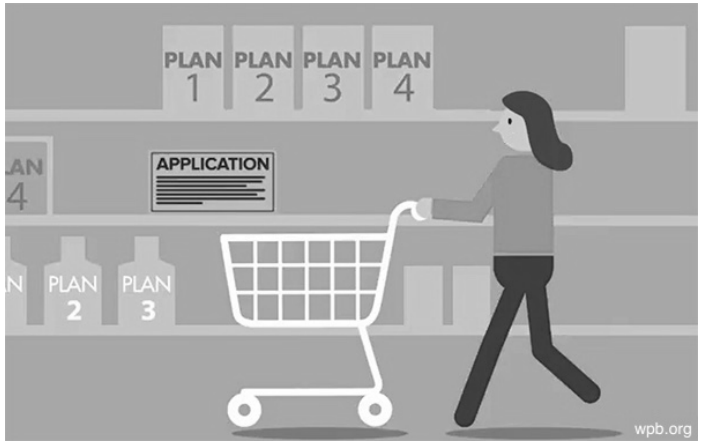

$$Y = \theta X$$

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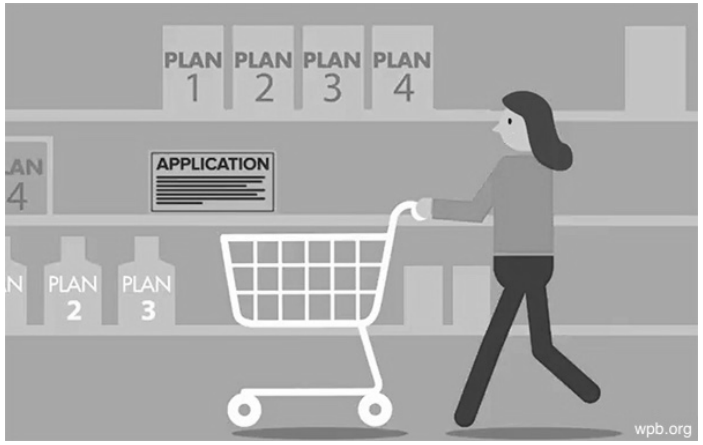

Spending outcome

$$Y = \theta X$$

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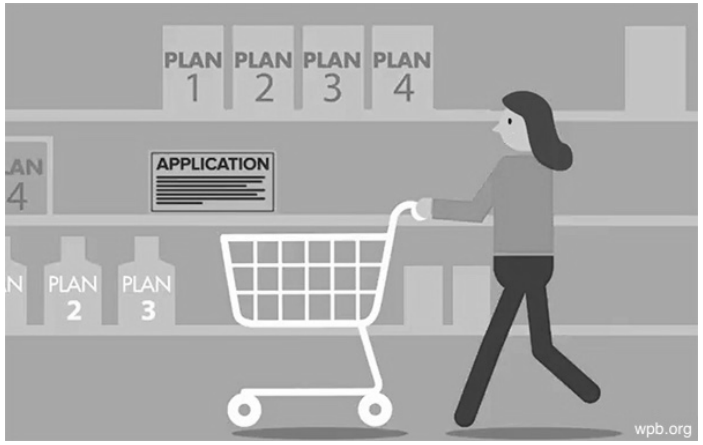

Spending outcome

$$Y = \theta X$$

Input vector

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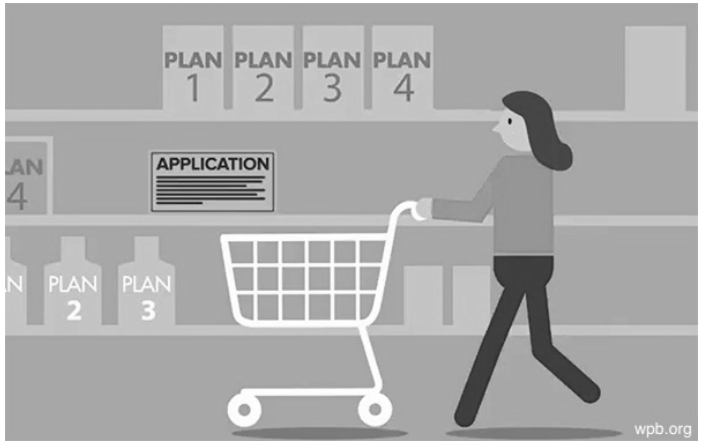

Spending outcome

$$Y = \theta X$$

Coefficient vector

Input vector

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Medicare upcoding and hospital ownership

Elaine Silverman[a,b], Jonathan Skinner[b,c,*]

[a] *Dartmouth Medical School, Hanover, NH 03755, USA*
[b] *Department of Economics, Dartmouth College, Hanover, NH 03755, USA*
[c] *National Bureau of Economic Research, Cambridge, MA 03755, USA*

Received 1 July 2003; accepted 1 September 2003

Abstract

Many hospitals in the 1990s many hospitals were accused of "upcoding" patient diagnostic related groups (DRGs) to increase Medicare reimbursements. We find that between 1989 and 1996, the percentage point share of the most generous DRG for pneumonia and respiratory infections rose by 10 points among not-for-profit hospitals, 23 points among for-profit hospitals, and 37 points in hospitals converting to for-profit status. Not-for-profit upcoding was also higher in markets with a larger for-profit hospital share. Upcoding appears to reflect both risk-taking by administrators and a closer alignment between the goals of the administration and the behavior of the clinical staff.
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Upcoding or Selection?

Evidence from Medicare on Squishy Risk Adjustment*

Michael Geruso† Timothy Layton‡

December 17, 2014

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WHISTLEBLOWER INFO

SEARCH

Qui Tam | Whistleblowers | False Claims Act | Medicare and Medicaid Fraud | Securities Fraud | Tax Fraud | Qui Tam Timeline

+ Qui Tam
+ Whistleblowers
+ False Claims Act
− Medicare and Medicaid Fraud

What is Medicare Fraud?
Medicare Fraud: Kickbacks
Famous Healthcare Whistleblower Lawsuits
Famous Healthcare Whistleblower Lawsuits
How to Report Healthcare Fraud
How to Report Kickback-Related Medicare Fraud
How to Report Off-Label Drug Marketing Fraud
How to Report Upcoding-Related Medicare Fraud
Medicare Fraud: Kickbacks

How to Report Upcoding-Related Medicare Fraud

The practice of "upcoding" in the submission of claims to the Medicare program is fraudulent and illegal. "Upcoding" is a term that describes the improper use of a billing code for a medical procedure or diagnosis that results in a higher payment to the medical provider than that warranted by the true procedure or diagnosis. Healthcare providers use specific codes to bill Medicare for particular services performed. The coding system used is called the Healthcare Common Procedure Coding System (HCPCS). Billing is done electronically and is processed by intermediary insurance companies on behalf of Medicare. Claims are then paid by these insurance carriers with government funds.

Due to the complexity of this coding system and the electronic, rather than personal, review of such claim submissions, close examination of each code billed for is nearly impossible. Medicare randomly audits approximately 2% of submitted claims. The lack of close monitoring of electronically submitted claims combined with almost non-existent post-submission auditing makes the Medicare billing system ripe for abuse. The cost of Medicare and Medicaid fraud to the federal government is estimated to be in the billions of dollars.

The practice of upcoding by a medical provider is usually revealed through the reporting of information of the fraud by an individual with first-hand knowledge or suspicion. The individual might be a medical professional with direct knowledge of an ongoing upcoding practice, or a Medicare beneficiary who notices a discrepancy on their Medicare Summary Notice. There are several avenues for reporting suspected cases of upcoding.

The official website of the Medicare program (www.Medicare.gov) provides instructions on how beneficiaries can report suspected Medicare fraud. Beneficiaries are instructed to review their Medicare Summary Notice and contact the medical provider to discuss the discrepancy. If the beneficiary is not

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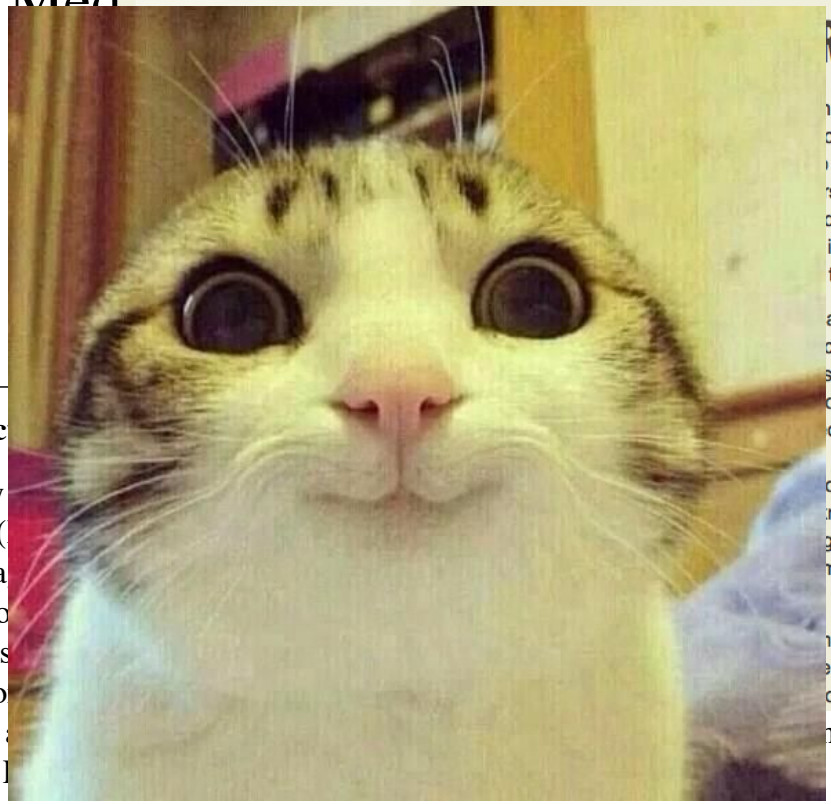
Med



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Risk Adjustment*

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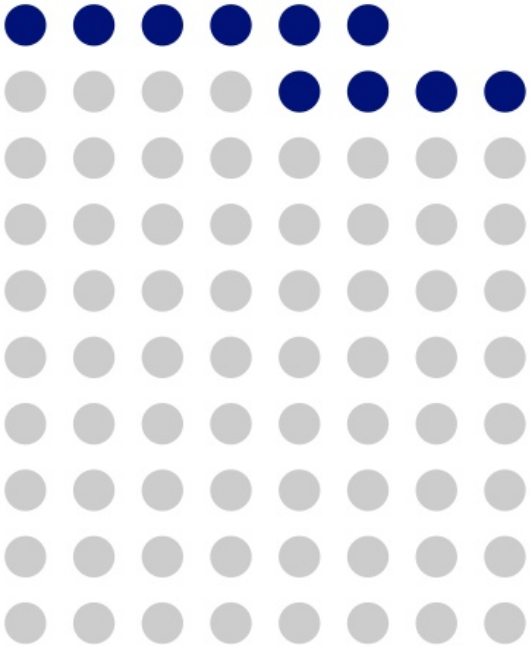
Variable Selection and Upcoding

Reduced set of 10 variables 92% as efficient

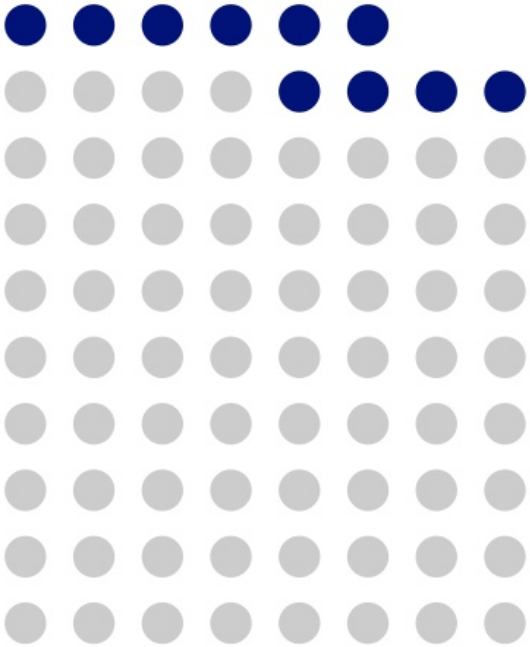


A Machine Learning Framework for Plan Payment Risk Adjustment

Sherri Rose

Variable Selection and Upcoding

~~Reduced set of 10 variables 92% as efficient~~



"…results for the risk adjustment algorithms that considered a limited subset of variables…performed consistently worse across all benchmarks."

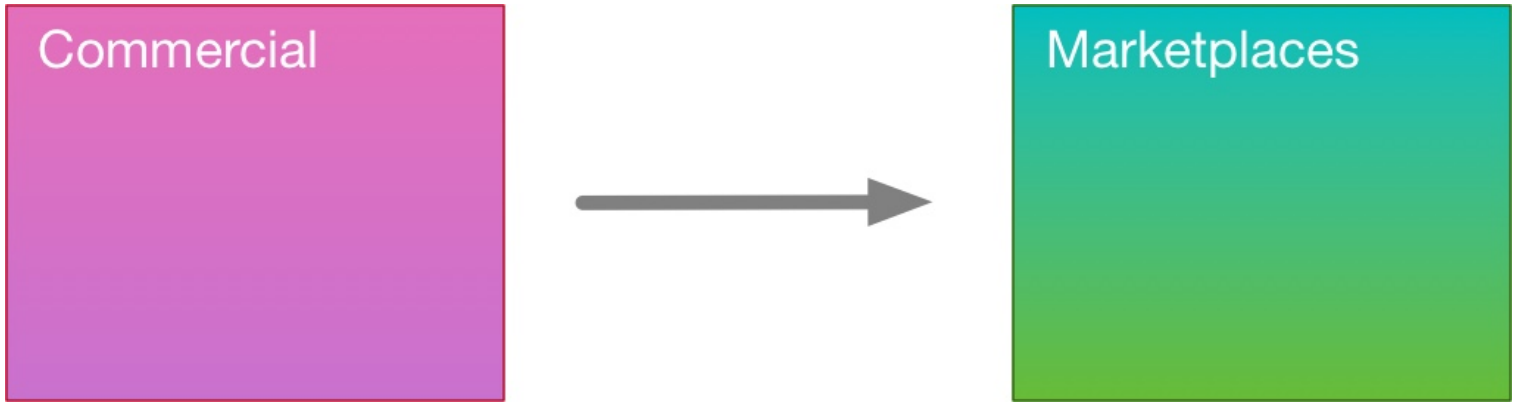
Sample Selection for Medicare Risk Adjustment Due to Systematically Missing Data

Savannah L. Bergquist, Thomas G. McGuire, Timothy J. Layton, and Sherri Rose

A Machine Learning Framework for Plan Payment Risk Adjustment

Sherri Rose

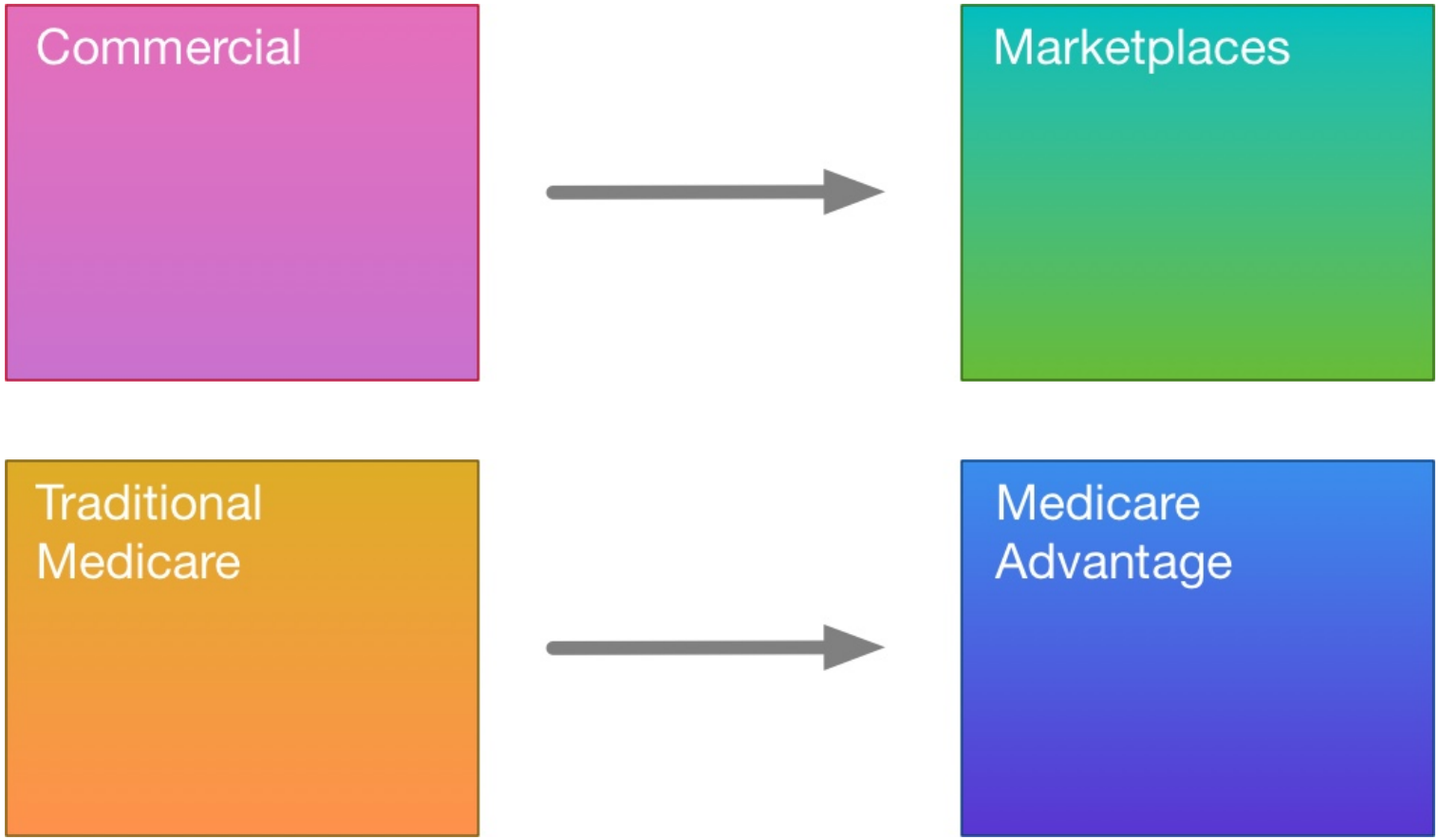
Prediction Using the "Wrong" Data



Matching and Imputation Methods for Risk Adjustment in the Health Insurance Marketplaces

Sherri Rose Julie Shi Thomas G. McGuire
Sharon-Lise T. Normand

Prediction Using the "Wrong" Data



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Matching and Imputation Methods for Risk Adjustment in the Health Insurance Marketplaces

Sherri Rose Julie Shi Thomas G. McGuire Sharon-Lise T. Normand

FAIRNESS

Prediction
Clustering
Inference
Generalizability
Fairness

Who decides the research question?

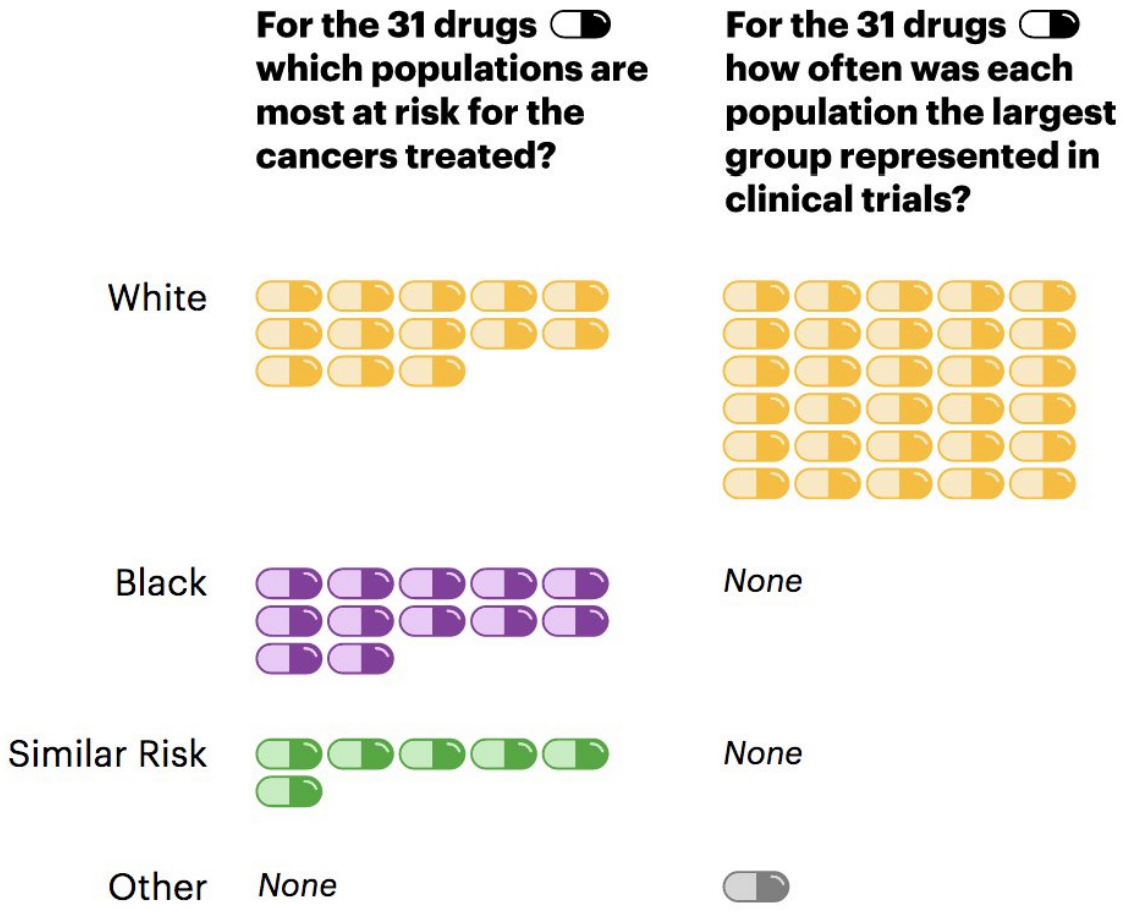
Who is in the target population?

What do the data reflect?

How will the algorithm be assessed?

Black Patients Miss Out On Promising Cancer Drugs

A ProPublica analysis found that black people and Native Americans are under-represented in clinical trials of new drugs, even when the treatment is aimed at a type of cancer that disproportionately affects them.



Note: Drugs are labeled "Similar Risk" if black Americans are at least 80 percent as likely as white Americans to be diagnosed with the cancer treated.

Chen and Wong (2018)

Black Patients Miss Out On Promising Cancer Drugs

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For the 31 drugs which populations are most at risk for the cancers treated?

For the 31 drugs how often was each population the largest group represented in clinical trials?

Research Letter

ONLINE FIRST FREE

September 28, 2020

The Exclusion of Older Persons From Vaccine and Treatment Trials for Coronavirus Disease 2019—Missing the Target

Benjamin K. I. Helfand, MSc[1,2]; Margaret Webb, BA[3]; Sarah L. Gartaganis, MSW, MPH[3]; et al

None

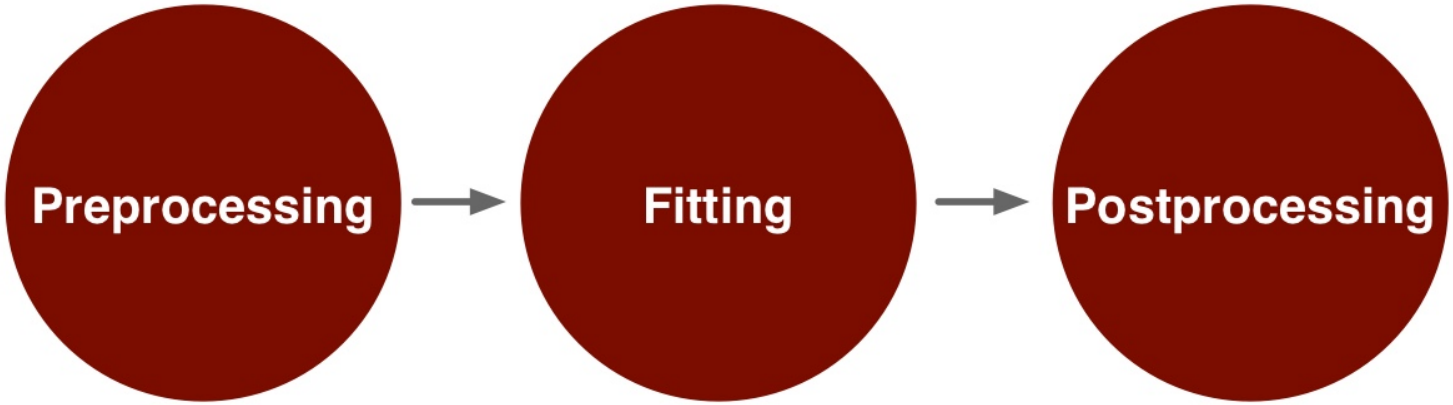
None

Other *None*

Note: Drugs are labeled "Similar Risk" if black Americans are at least 80 percent as likely as white Americans to be diagnosed with the cancer treated.

Chen and Wong (2018)

Fairness

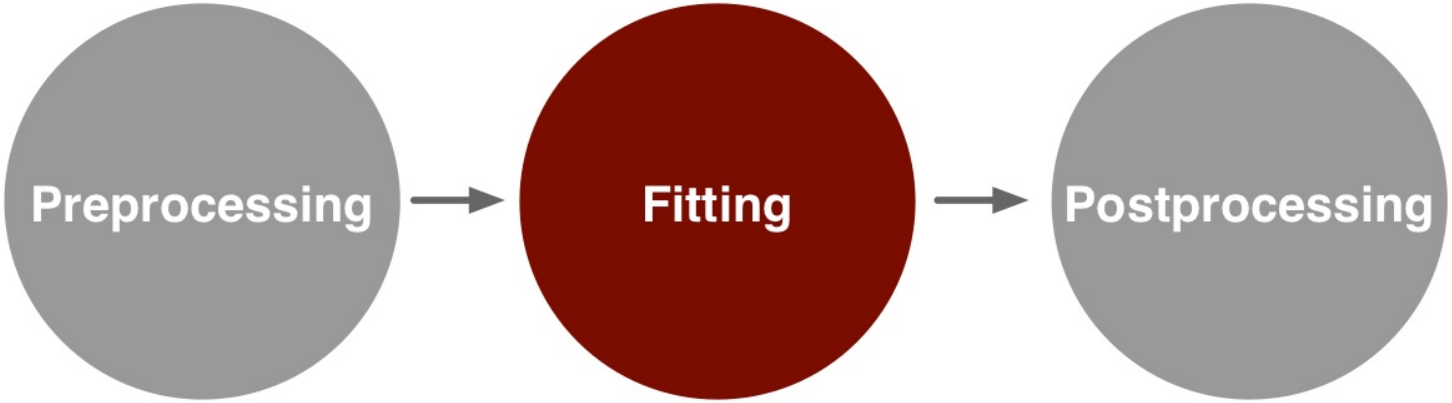


Fairness

Data transformations

Health Economics	
Newhouse (2002) Layton et al. (2016) **Bergquist et al. (2018)**	Kamiran and Calders (2009) Zliobaite et al. (2011) Zemel et al. (2013) Calmon et al. (2017) Johndrow and Lum (2017)

Fairness

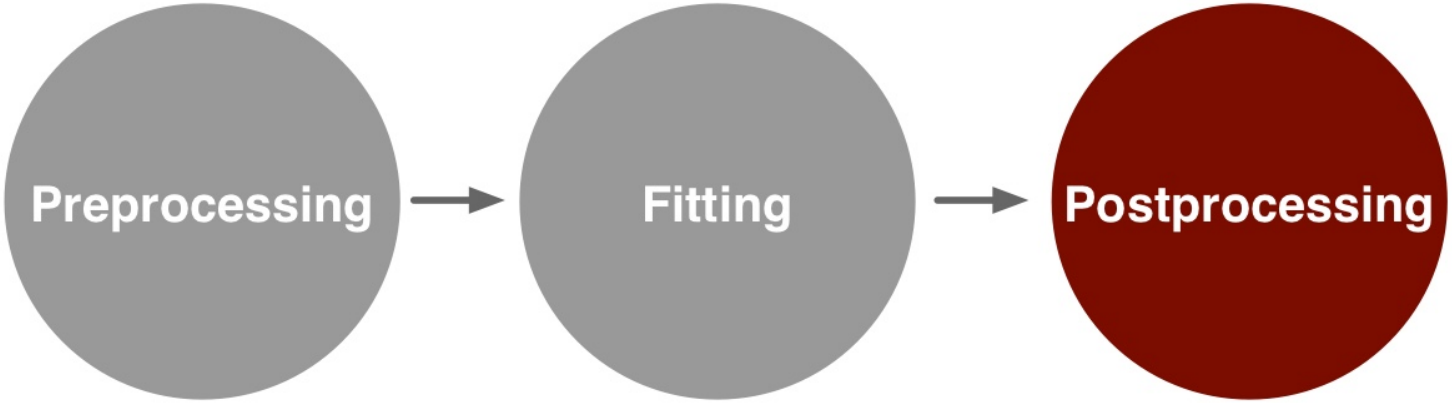


Adding variables, separate formulas, statistical learning

van Kleef et al. (2013)
Rose (2016)
van Kleef et al. (2017)
Shrestha et al. (2018)
van Kleef et al. (2018)

Kamishima et al. (2012)
Berk et al. (2017)
Zafar et al. (2017a,b)
Bechavod and Ligett (2018)
Dwork et al. (2018)

Fairness



Reinsurance, differing thresholds

e.g., McGuire et al. (2018)

Bansal et al. (2014)
Hardt et al. (2016)
Kleinberg et al. (2018)
El Mhamdi et al. (2018)

Algorithmic Fairness

Typical algorithmic fairness problem in computer science has

- outcome Y
- vector X that includes a protected class or sensitive attribute $A \subset X$

Goal:

Create estimator for $f(X) = Y$ while ensuring the function is fair for A

Common measures of fairness are based on the notion of **group fairness**, striving for similarity in predicted outcomes or errors for groups

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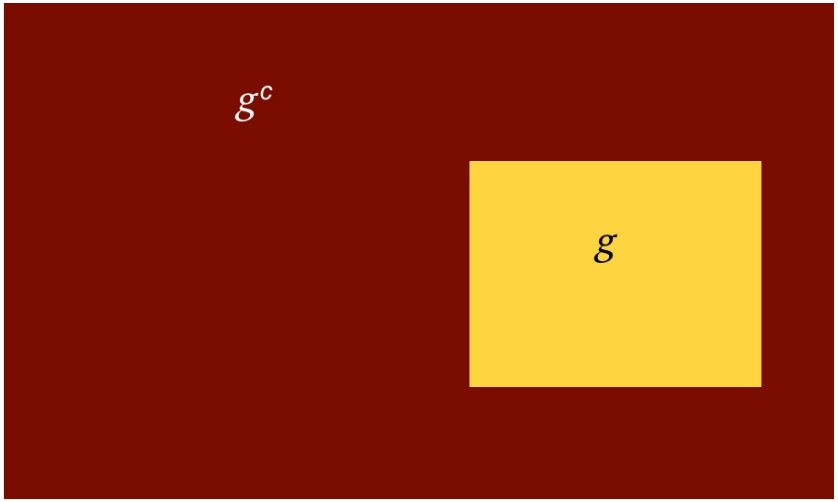
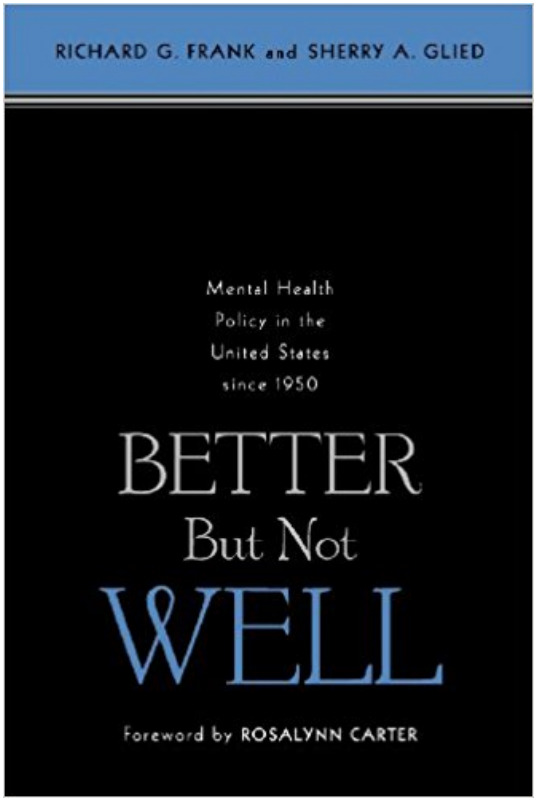


Improving Mental Health Care, 1950-2000

Changes in financing and organization of mental health care, not new treatment technologies, made the difference

"Improvements ... evolved through ... more money, greater consumer choice, and the increased competition among ... providers that these forces unleashed"



HealthAffairs

Mental Disorders Top The List Of The Most Costly Conditions In The United States: $201 Billion

Charles Roehrig

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HealthAffairs

Which Medical Conditions Account For The Rise In Health Care Spending?

Kenneth E. Thorpe, Curtis S. Florence, and Peter Joski

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HSR Health Services Research

Robust Machine Learning Variable Importance Analyses of Medical Conditions for Health Care Spending

Sherri Rose

Mental Health and Substance Use Disorders (MHSUD)

Risk adjustment in the Marketplaces
recognizes only 20% of enrollees with MHSUD

Individuals with MHSUD can be **systematically discriminated** against

By Ellen Montz, Tim Layton, Alisa B. Busch, Randall P. Ellis, Sherri Rose, and Thomas G. McGuire

Risk-Adjustment Simulation: Plans May Have Incentives To Distort Mental Health And Substance Use Coverage

Large Gains in Group Fairness vs. OLS

Regression Method	R^2	MHSUD Net Compensation
Average	12.4%	
Covariance	12.4	
Net Compensation	12.5	
Weighted Average	12.6	
Mean Residual Difference	12.8	
Ordinary Least Squares	12.9	

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Fair regression for health care spending

Anna Zink, Sherri Rose

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4%

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Large Gains in Group Fairness vs. OLS

Regression Method	R^2	MHSUD Net Compensation
Average	12.4%	-$46
Covariance	12.4	-46
Net Compensation	12.5	-232
Weighted Average	12.6	-411
Mean Residual Difference	12.8	-1208
Ordinary Least Squares	12.9	-1872

98%

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Fair regression for health care spending

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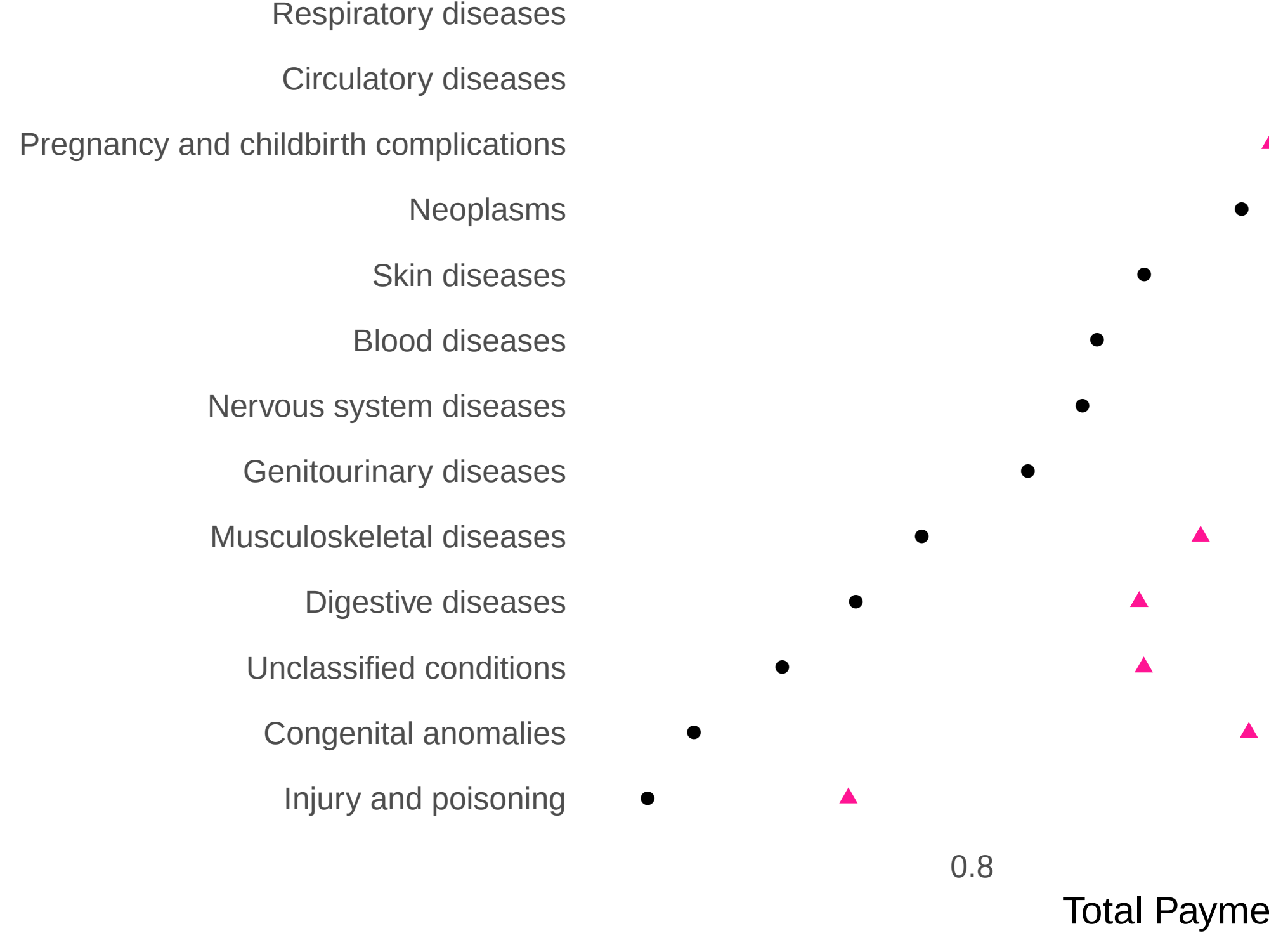
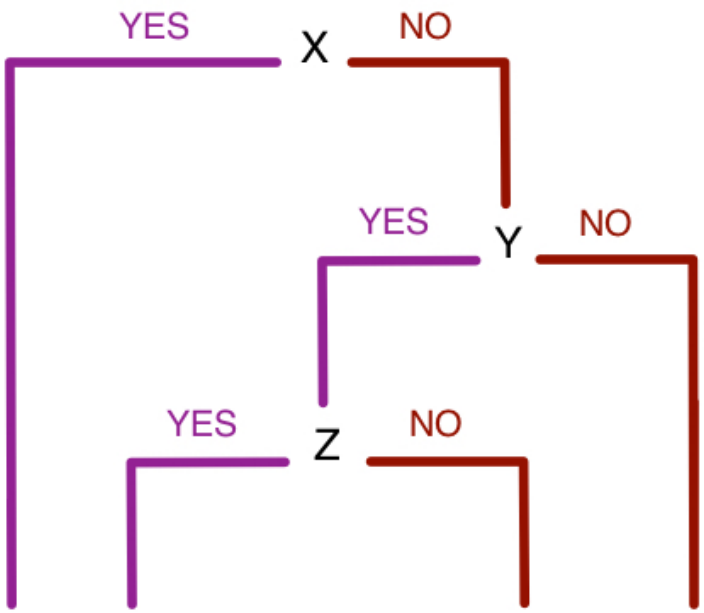

Respiratory diseases
Circulatory diseases
Pregnancy and childbirth complications
Neoplasms
Skin diseases
Blood diseases
Nervous system diseases
Genitourinary diseases
Musculoskeletal diseases
Digestive diseases
Unclassified conditions
Congenital anomalies
Injury and poisoning
0.8
Total Payme

Discovering Groups

Anna Zink
PhD Student
Harvard



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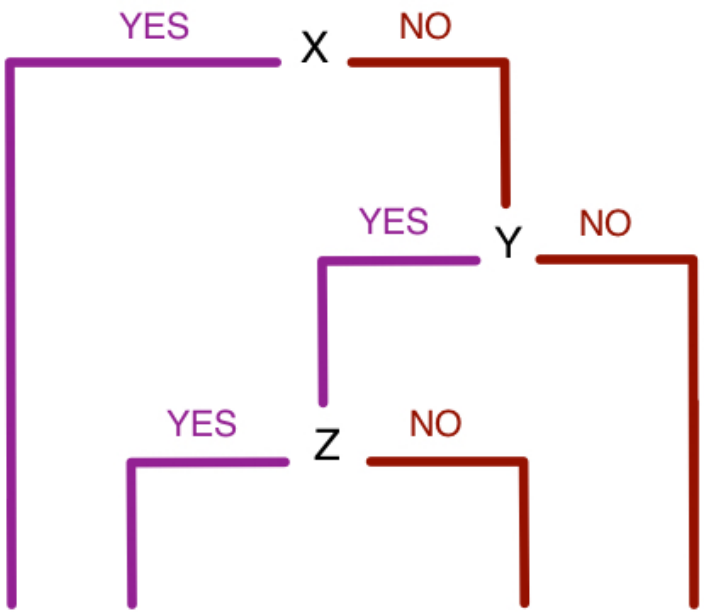

Example Hypothetical Group

Discovering Groups

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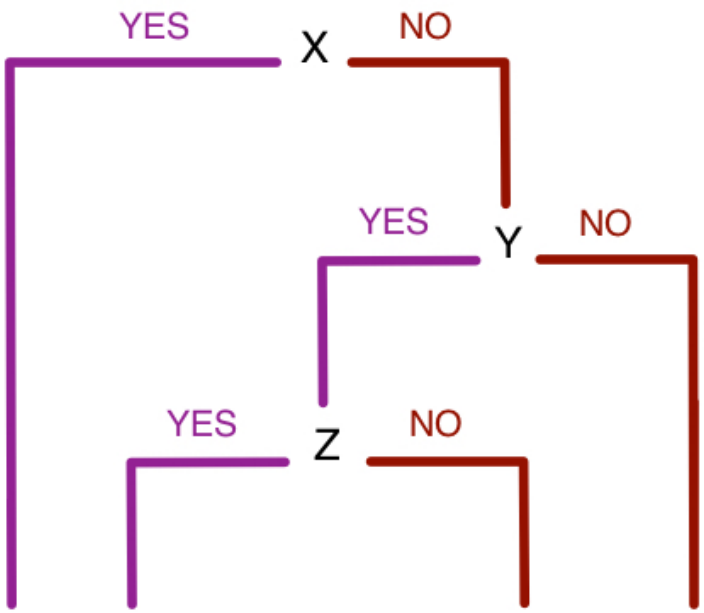

Example Hypothetical Group

AGE 55 to 59

Discovering Groups

Anna Zink
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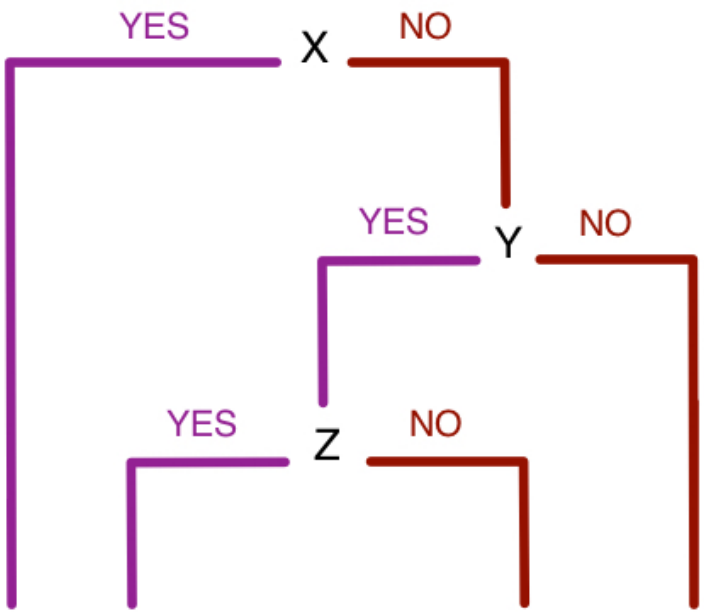

Example Hypothetical Group

AGE 55 to 59

Discovering Groups

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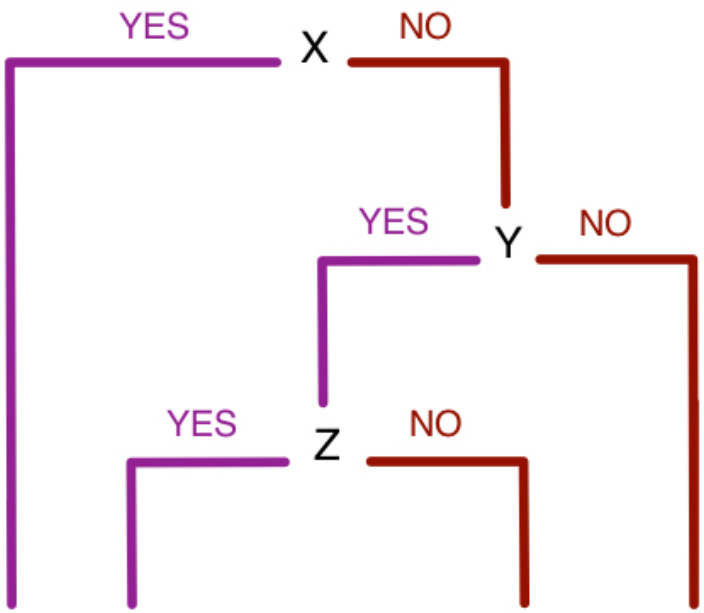


Example Hypothetical Group

AGE 55 to 59

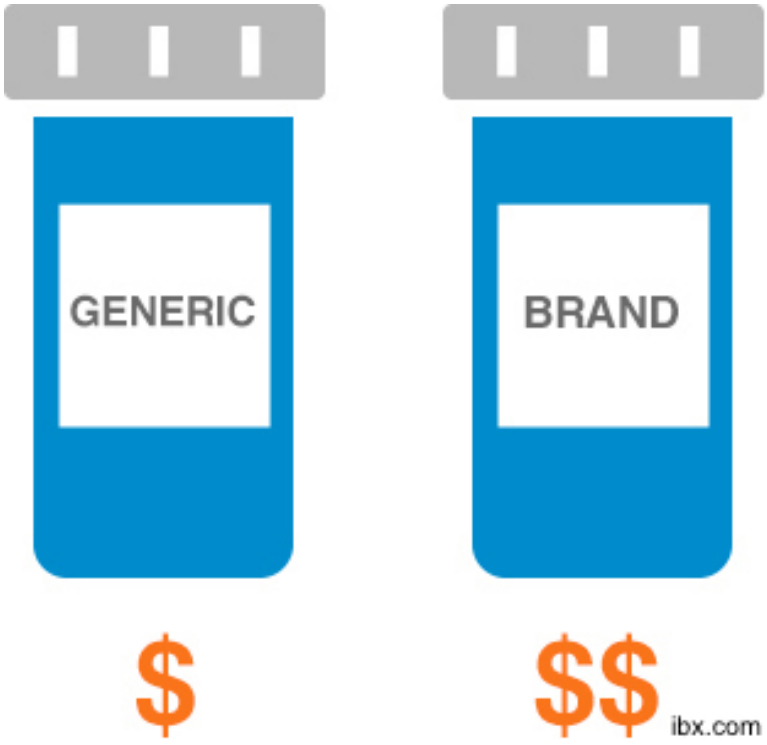
Undercompensated?

HUMANS + MACHINES

Predicting Unprofitability

Profit-Maximizing Insurer:

- Design plan to attract profitable & deter unprofitable enrollees
- Cannot discriminate based on pre-existing conditions
- Raise/lower out of pocket costs of drugs for some conditions
- Distortions make it difficult for unprofitable groups to find acceptable coverage



Demonstrate drug formulary identifies unprofitable enrollees

Computational health economics for identification of unprofitable health care enrollees

Sherri Rose ✉, Savannah L. Bergquist, Timothy J. Layton

Predicting Unprofitability

- Limit to ∼10 non-zero variables
- Augment with therapeutic classes for HIV & multiple sclerosis drugs

```r
# lasso screener that always retains classes for HIV and MS drugs
var.index <- c(which(colnames(newdat)=="tcls14"), which(colnames(newdat)=="tcls251"))

screen.glmnet10 <- function(Y, X, family, alpha = 1, minscreen = 2, nfolds = 10, nlambda = 100,fixed.var.index=var.index,...) {
  # .SL.require('glmnet')
  if(!is.matrix(X)) {
    X <- model.matrix(~ -1 + ., X)
  }
  fitCV <- glmnet::cv.glmnet(x = X, y = Y, lambda = NULL, type.measure = 'deviance',
                             nfolds = nfolds, family = family$family, alpha = alpha,
                             nlambda = nlambda, pmax=10, parallel=T)
  whichVariable <- (as.numeric(coef(fitCV$glmnet.fit, s = fitCV$lambda.min))[-1] != 0)
  # the [-1] removes the intercept; taking the coefs from the fit w/ lambda that gives minimum cvm
  if (sum(whichVariable) < minscreen) {
    warning("fewer than minscreen variables passed the glmnet screen,
            increased lambda to allow minscreen variables")
    sumCoef <- apply(as.matrix(fitCV$glmnet.fit$beta), 2, function(x) sum((x != 0)))
    newCut <- which.max(sumCoef >= minscreen)
    whichVariable <- (as.matrix(fitCV$glmnet.fit$beta)[, newCut] != 0)
  }
  whichVariable[c(var.index)] <- TRUE
  return(whichVariable)
}
```

sl-bergquist.github.io/unprofits

POLICY AND PRACTICE

Can Your Hip Replacement Kill You?

By JEANNE LENZER JAN. 13, 2018

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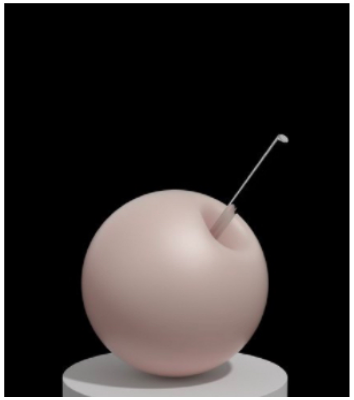
TheUpshot

Why Medical Devices Aren't Safer

Austin Frakt
THE NEW HEALTH CARE APRIL 18, 2016



Things sometimes go wrong with airbags, food and drugs, prompting recalls. It can also happen with medical devices, though you'd think lifesaving devices like heart defibrillators or artificial hips would be closely monitored.

But the data needed to systematically and rapidly identify dangerous medical devices are not routinely collected in the United States.

SundayReview | OPINION

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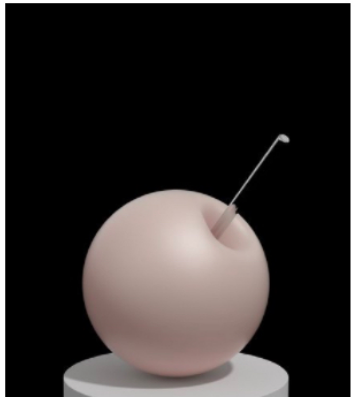

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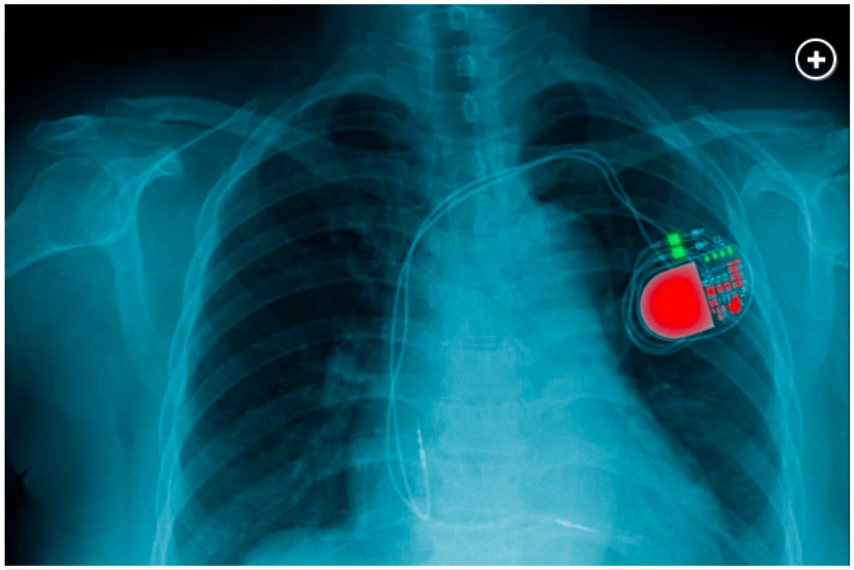
Your medical implant could kill you

By Jeanne Lenzer December 16, 2017 | 12:08pm | Updated



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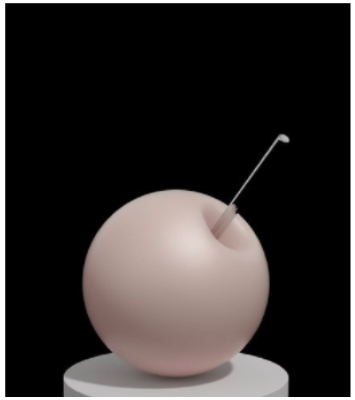

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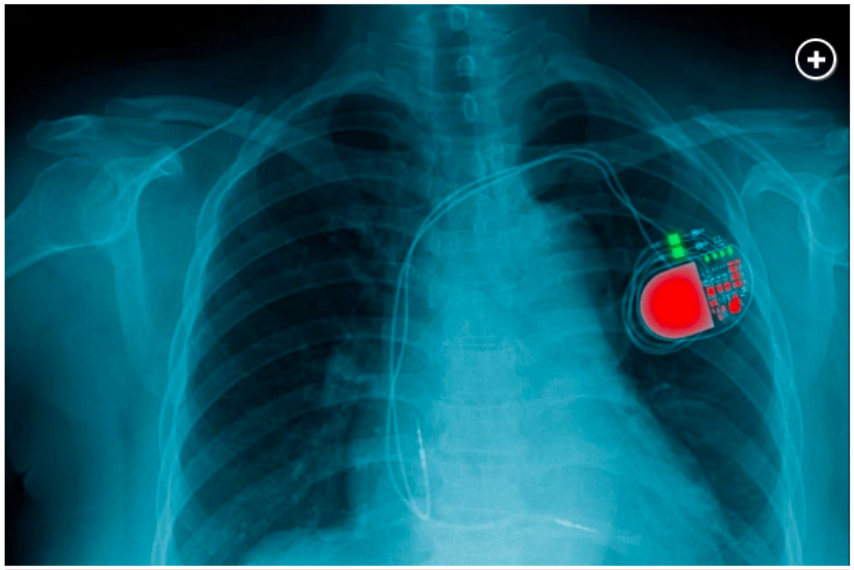

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MEDICAL TREATMENTS

Are Implanted Medical Devices Creating A 'Danger Within Us'?

36:19

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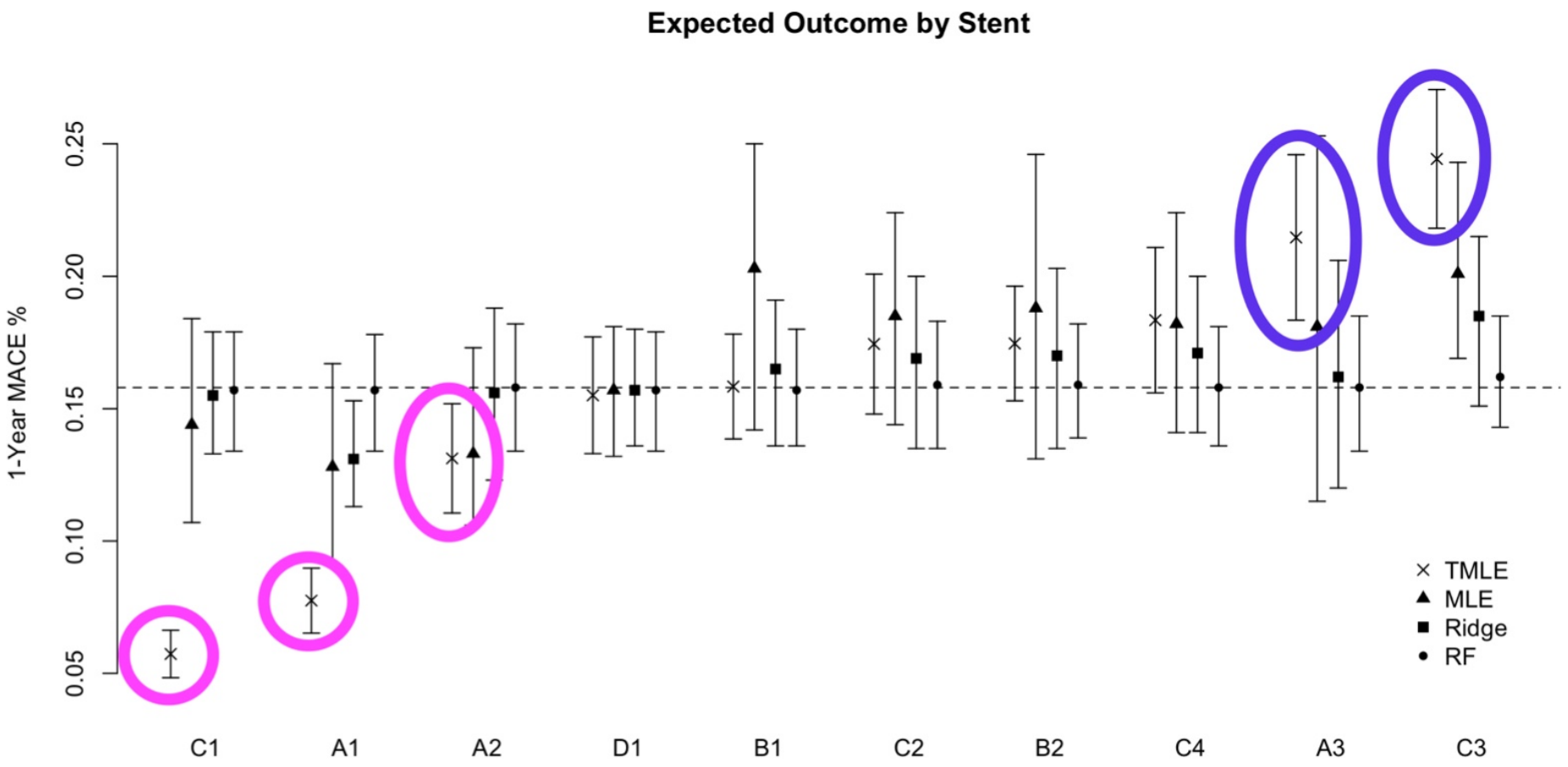
January 17, 2018 · 3:10 PM ET
Heard on Fresh Air

DAVE DAVIES

FRESH AIR

Medical journalist Jeanne Lenzer warns that implanted medical devices are approved with far less scrutiny and testing than drugs. As a result, she says, some have caused harm and even death.

Cardiac Stent Results



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Double robust estimation for multiple unordered treatments and clustered observations: Evaluating drug-eluting coronary artery stents

Sherri Rose, Sharon-Lise Normand

Cardiac Stent Policy Implications

Implications for patients, hospitals, manufacturers, and regulators.

- How can this information be incorporated into the patient's decision-making process?
- Will hospitals reconsider their complex contracting with manufacturers to avoid poorer-performing devices?
- Should manufacturers consider pulling stents from the market?
- How should regulators respond to postmarket information that was not available at the time of device approval?

IN CLOSING

Health Care Spending

The American Journal of Psychiatry

Patient Casemix Classification for Medicare Psychiatric Prospective Payment

Edward M. Drozd Ph.D.Jerry Cromwell Ph.D.Barbara Gage Ph.D.Jan Maier R.N., M.P.H.
Leslie M. Greenwald Ph.D.Howard H. Goldman M.D.

HSR HEALTH SERVICES RESEARCH
Impacting Health Practice and Policy Through State-of-the-Art Research and Thinking

Regression Tree Boosting to Adjust Health Care Cost Predictions for Diagnostic Mix

John W. Robinson

Health Care Quality

American Economic Review: Papers & Proceedings 2017, 107(5): 476–480

UNITED STATES HEALTH CARE FROM VARIOUS PERSPECTIVES

Does Machine Learning Automate Moral Hazard and Error?

By Sendhil Mullainathan and Ziad Obermeyer*

Epidemiology. 28(2):237–248

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Sebastian Schneeweiss;Wesley Eddings;Robert Glynn;Elisabetta Patorno;Jeremy Rassen;Jessica Franklin;

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Health Economics / Volume 24, Issue 9

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Policy Evaluation

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NBER
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Policy Evaluation

International Journal of
Epidemiology

Intersections of machine learning and epidemiological methods for health services research

Sherri Rose

Does Your Algorithm Have a Social Impact Statement?

Responsibility

Explainability

Accuracy

Auditability

Fairness

fatml.org/resources/principles-for-accountable-algorithms

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Harvard

Irina Degtiar
Harvard

Noémie Sportiche
Harvard

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