Ensembles for Prediction and Causal Inference

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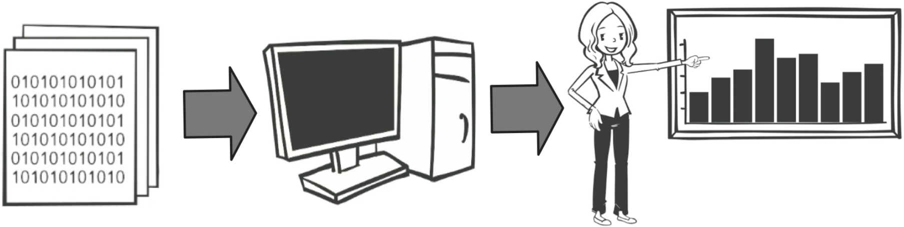
Department of Health Care Policy
Harvard Medical School

drsherrirose.com · @sherrirose

June 25, 2018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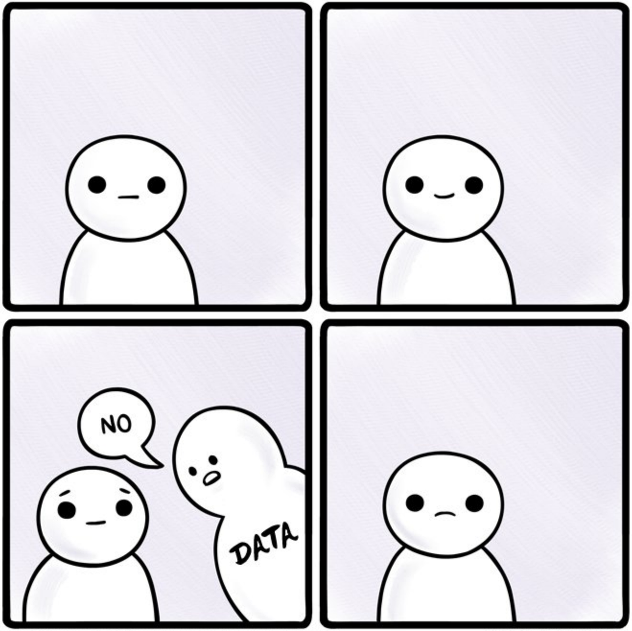

THIS COMIC MADE POSSIBLE THANKS TO ADAM LINGELBACH

MRLOVENSTEIN.COM

Electronic Health Databases

The increasing availability of electronic medical records 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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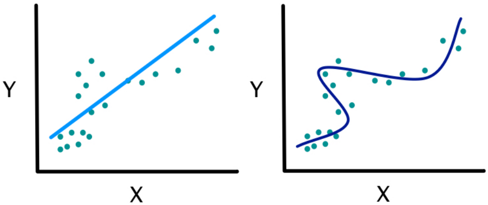
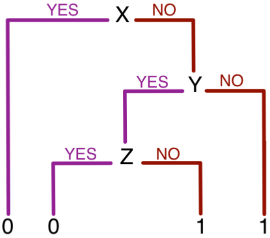
Need **novel statistical methods** that have desirable properties while remaining computationally feasible

We've Discussed Prediction



Machine learning aims to

- "smooth" over the data
- make fewer assumptions
- $n > p$
- handle data sparsity



Prediction: Options?

- Recent studies for prediction have employed newer **algorithms.**
  (any mapping from data to a predictor)

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  - *"When should I use random forest instead of standard regression?"*

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ELSEVIER

Journal of Clinical Epidemiology 63 (2010) 1145–1155

Journal of Clinical Epidemiology

Logistic regression had superior performance compared with regression trees for predicting in-hospital mortality in patients hospitalized with heart failure

Peter C. Austin[a,c,*], Jack V. Tu[a,b,c,d,e], Douglas S. Lee[a,e,f]

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Peter C. Austin[a,c,*], Jack

European Journal of Neurology 2010, **17:** 945–950

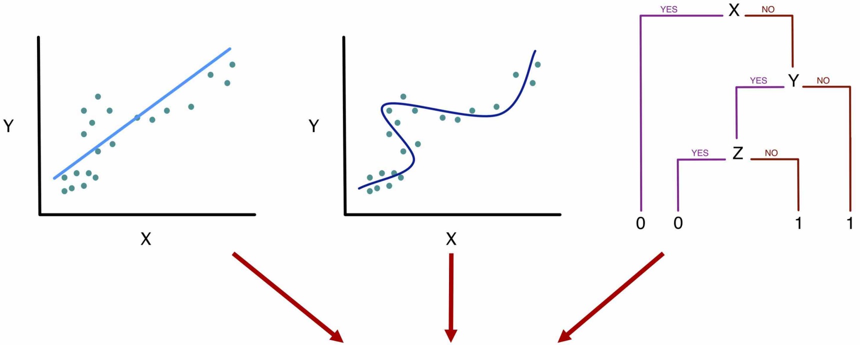
doi:10.1111/j.1468-1331.2010.02955.x

Random forest can predict 30-day mortality of spontaneous intracerebral hemorrhage with remarkable discrimination

S. -Y. Peng[a,b,c], Y. -C. Chuang[b], T. -W. Kang[b] and K. -H. Tseng[d]

[a]*Institute of Biomedical Informatics, National Yang-Ming University, Taipei;* [b]*Department of Anesthesiology, Taichung Veterans General Hospital, Taichung;* [c]*School of Medicine, Chung Shan Medical University, Taichung; and* [d]*Department of Nephrology, Taoyuan Veterans Hospital, Taoyuan, Taiwan*

Prediction: Ensembles



Weighted Average

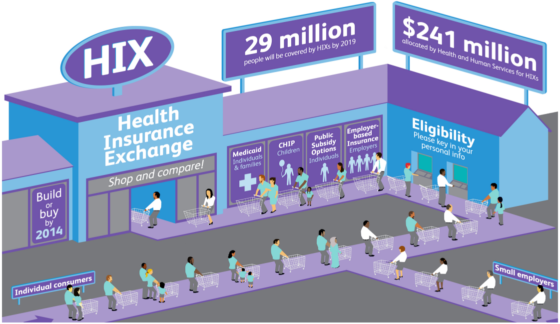
Ensembles

Risk Adjustment in Plan Payment

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

- Redistributes funds based on health
- Encourages competition based on efficiency & quality
- Huge financial implications

Health Insurance Marketplace



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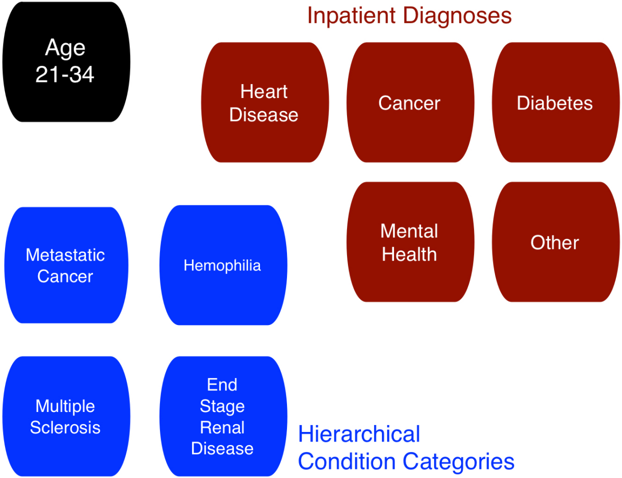
Risk Adjustment in Plan Payment

Machine Learning: Reduced set of 10 variables 92% as efficient.

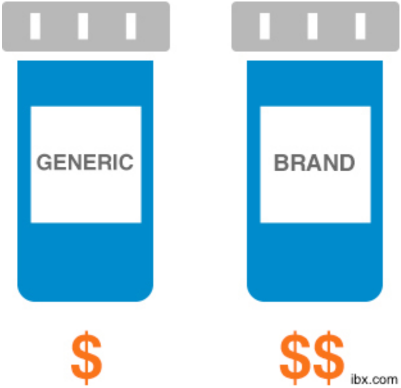


Rose (2016). *Health Services Research.*

Risk Adjustment in Plan Payment

Profit-Maximizing Insurer:

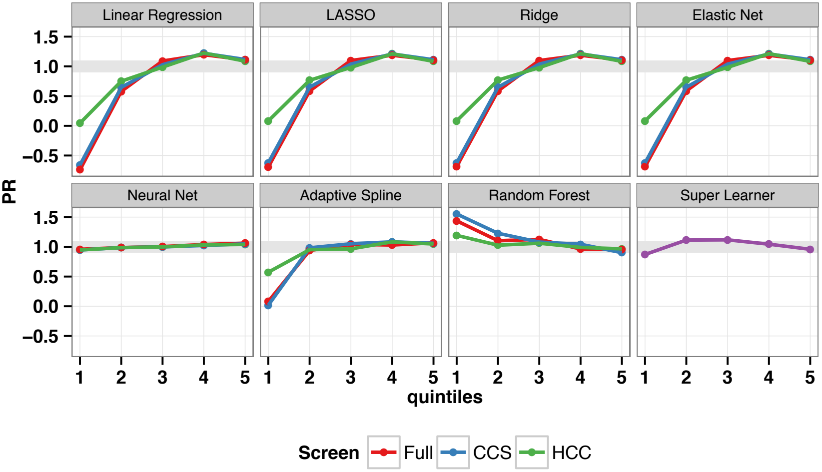
- Design plan to attract profitable enrollees and deter unprofitable
- Cannot discriminate based on pre-existing conditions
- Raise/lower out of pocket costs of drugs for some conditions
- Distortions make it difficult for unprofitable groups to find acceptable coverage



Demonstrate drug formulary identifies unprofitable enrollees

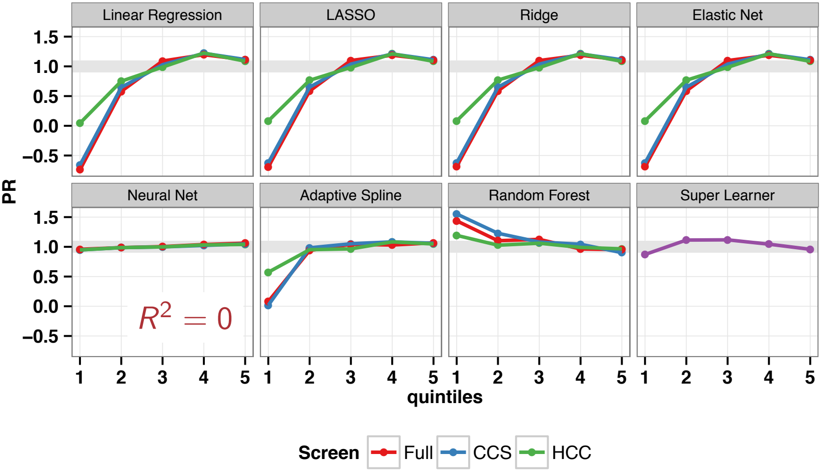
Rose, Bergquist, Layton (2017). *Biostatistics*.

Risk Adjustment in Plan Payment



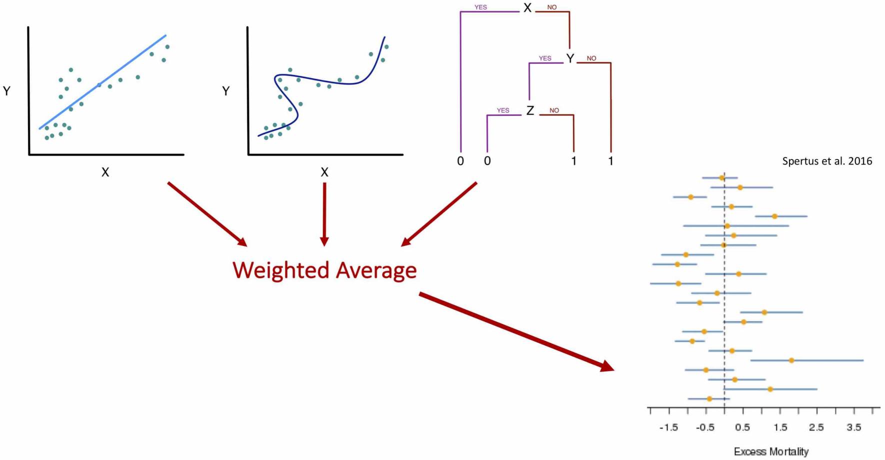
Shrestha, Bergquist, Montz, Rose (2017). *Health Services Research*.

Risk Adjustment in Plan Payment



Shrestha, Bergquist, Montz, Rose (2017). *Health Services Research*.

Machine Learning + Causal Effect Estimation



Machine Learning + Causal Effect Estimation

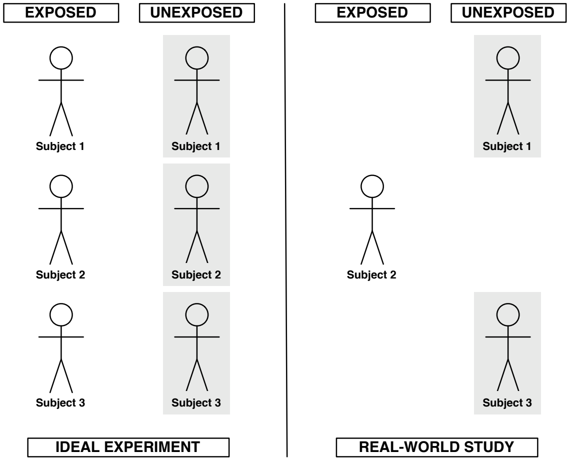


Image: Rose & van der Laan (2011)

Medical Devices

- National medical device system has been proposed
- Information to distinguish devices not currently routinely collected, nor available in medical claims (as it is for prescription drugs)

BROOKINGS

REPORT

Strengthening patient care: Building an effective national medical device surveillance system

Heather Colvin, **Pranav Aurora**, **Saha Khaterzai**, **Gregory W. Daniel**, and **Mark B. McClellan** ·
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Implantable medical devices represent **high-risk treatments** often evaluated in the premarket setting on the basis of **smaller trials**, are likely to **change quickly over time**, and have led to **serious side effects**.

Medical Devices

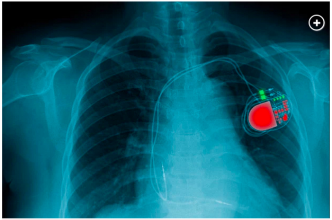
SundayReview | OPINION

Can Your Hip Replacement Kill You?

By JEANNE LENZER JAN. 13, 2018

Your medical implant could kill you

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



THE UPSHOT | Why Medical Devices Aren't Safer

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.

It wouldn't be that hard to do.

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MEDICAL TREATMENTS

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

36:19
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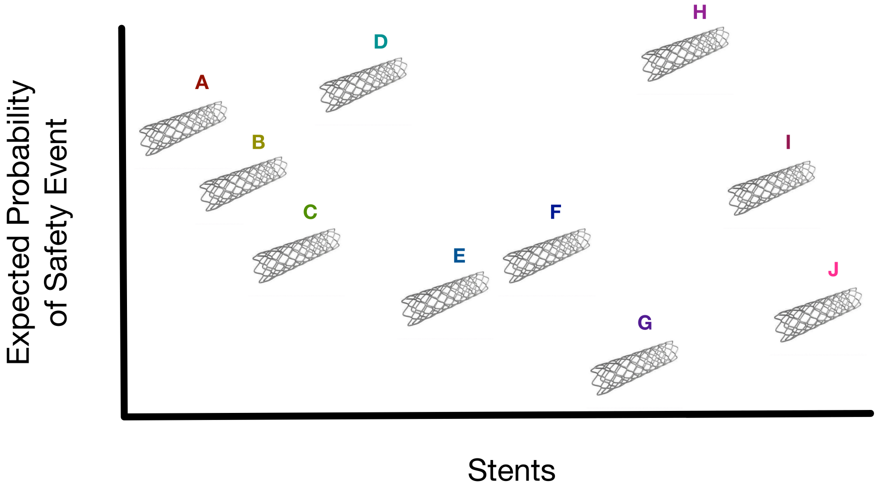
January 17, 2018 · 3:10 PM ET
Heard on Fresh Air

DAVE DAVIES

FRESH AIR

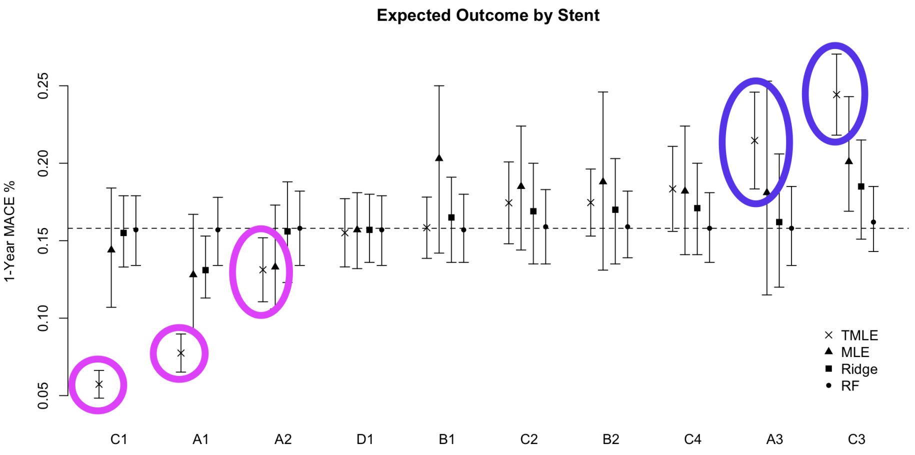
Medical journalist Jeanne Lenzer warns that implanted medical devices are approved with far less scrutiny and testing than drugs. As a result, she says, some have caused harm and even death.

Cardiac Stents



Stent logo: elmedicointeractivo.com

Cardiac Stents: Results



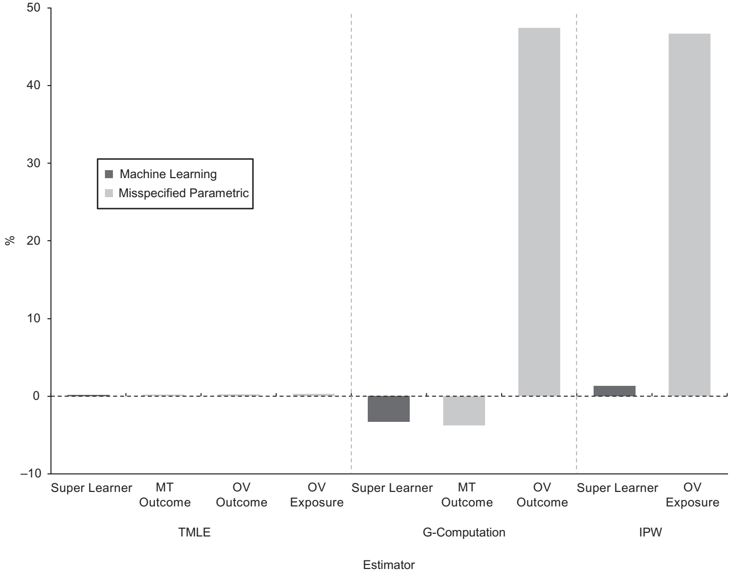
Rose and Normand (2018). *Biometrics*. Funding: NIH R01-GM111339.

Cardiac Stents: Policy Implications

Implications for patients, hospitals, device manufacturers, and regulators.

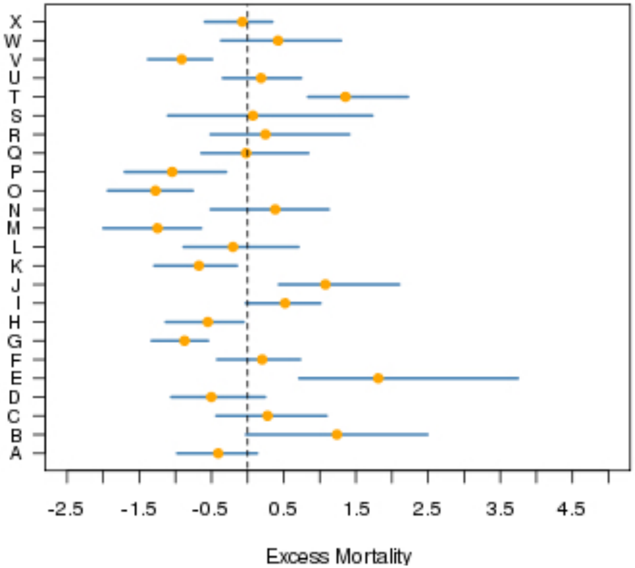
- How can this information be incorporated into the patient's decision-making process?
- Will hospitals reconsider their complex contracting with manufacturers to avoid poorer-performing devices?
- Should manufacturers consider pulling certain stents from the market?
- How should regulators respond to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

Causal Machine Learning Tutorial



Schuler and Rose (2017). *American Journal of Epidemiology*.

Hospital Profiling



Spertus et al. (2016). *Circulation: Cardiovascular Quality and Outcomes.*

Hospital Profiling

Method and Confounder Set	Low Mortality Hospitals	As-Expected Hospitals	High Mortality Hospitals
Regression-only clinical confounders	7	11	6
A-IPW clinical confounders	8	10	6
TMLE clinical confounders	7	13	4
Regression-only full confounders	7	13	4
A-IPW full confounders	7	13	4
TMLE full confounders	7	14	3

Spertus et al. (2016). *Circulation: Cardiovascular Quality and Outcomes*.

Difference-in Differences Parameters

Can we assess causality for **other common targets of inference?**

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For example, difference-in-differences parameters. We do a lot of these with parametric models:

The NEW ENGLAND JOURNAL of MEDICINE

SPECIAL ARTICLE

Changes in Health Care Spending and Quality 4 Years into Global Payment

Zirui Song, M.D., Ph.D., Sherri Rose, Ph.D., Dana G. Safran, Sc.D., Bruce E. Landon, M.D., M.B.A., Matthew P. Day, F.S.A., M.A.A.A., and Michael E. Chernew, Ph.D.

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The NEW ENGLAND JOURNAL of MEDICINE

SPECIAL ARTICLE

Early Performance of Accountable Care Organizations in Medicare

J. Michael McWilliams, M.D., Ph.D., Laura A. Hatfield, Ph.D., Michael E. Chernew, Ph.D., Bruce E. Landon, M.D., M.B.A., and Aaron L. Schwartz, Ph.D.

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OURNAL of MEDICINE

ARTICLE

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The NEW ENGLAND JOURNAL of MEDICINE

Original Investigation

FREE

November 2015

Changes in Low-Value Services in Year 1 of the Medicare Pioneer Accountable Care Organization Program

Aaron L. Schwartz, PhD[1]; Michael E. Chernew, PhD[1]; Bruce E. Landon, MD, MBA, MSc[1,2]; et al

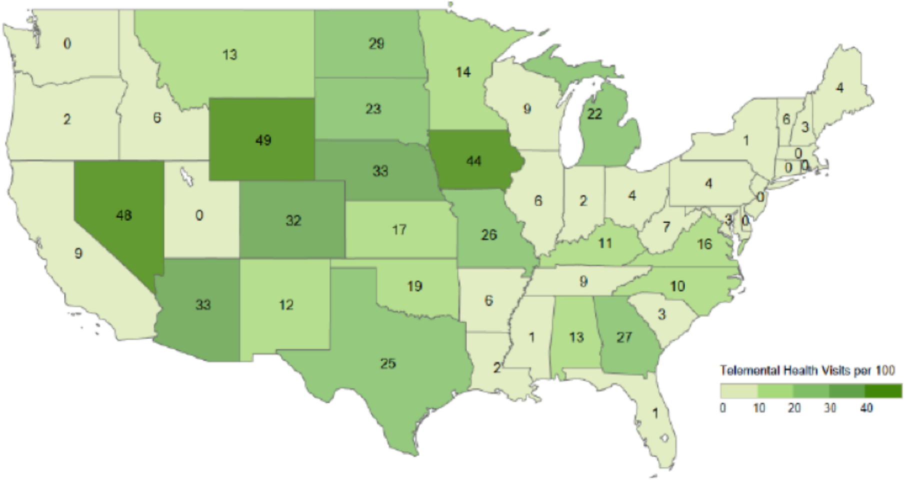
» Author Affiliations | Article Information

JAMA Intern Med. 2015;175(11):1815-1825. doi:10.1001/jamainternmed.2015.4525

Difference-in Differences Parameters

- 78% of telemedicine visits for mental health, 2004-14

Telemental Health Visits in Rural Medicare Patients with Serious Mental Illness



Study impact of telemental health on ED visits, hospitalization, adherence

Difference-in Differences Parameters

Statistics > Methodology

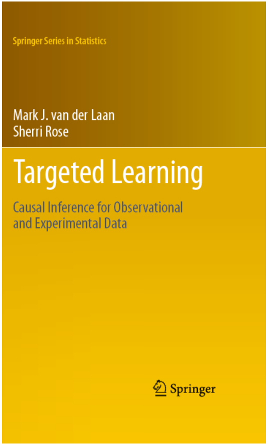
Stacked Propensity Score Functions for Observational Cohorts with Oversampled Exposed Subjects

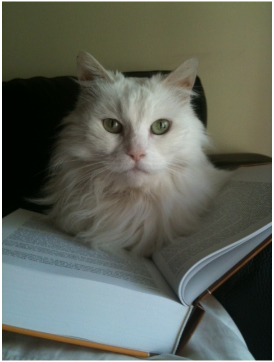
Sherri Rose

(Submitted on 20 May 2018)

Observational cohort studies with oversampled exposed subjects are typically implemented to understand the causal effect of a rare exposure. Because the distribution of exposed subjects in the sample differs from the source population, estimation of a propensity score function (i.e., probability of exposure given baseline covariates) targets a nonparametrically nonidentifiable parameter. Consistent estimation of propensity score functions is an important component of various causal inference estimators, including double robust machine learning and inverse probability weighted estimators. We propose the use of the probability of exposure from the source population in observation-weighted stacking algorithms to produce consistent estimators of propensity score functions. Simulation studies and a hypothetical health policy intervention data analysis demonstrate low empirical bias and variance for these stacked propensity score functions with observation weights.

Targeted Learning Methods

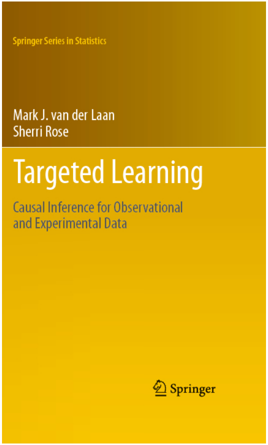


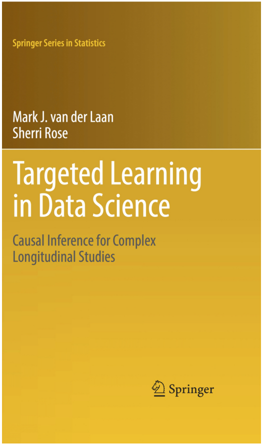


van der Laan & Rose, *Targeted Learning: Causal Inference for Observational and Experimental Data*. New York: Springer, 2011.

`targetedlearningbook.com`

Targeted Learning Methods

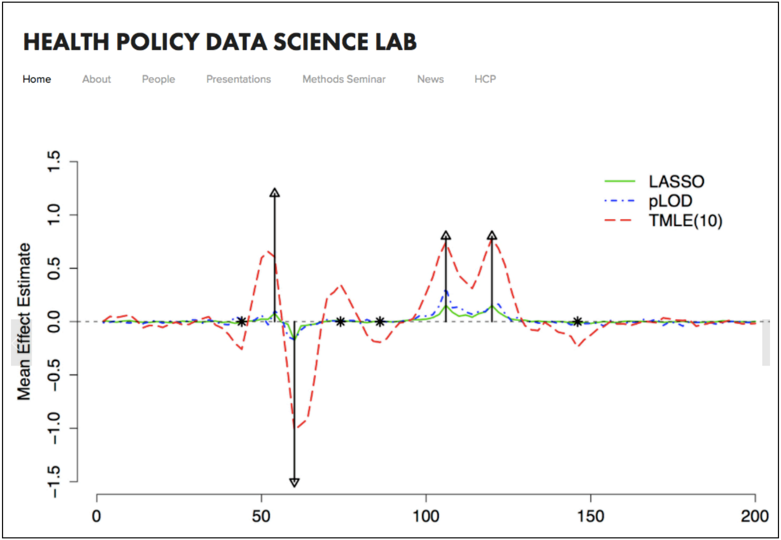




van der Laan & Rose, *Targeted Learning in Data Science: Causal Inference for Complex Longitudinal Studies*. New York: Springer, 2018.

`targetedlearningbook.com`

Health Policy Data Science Lab



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