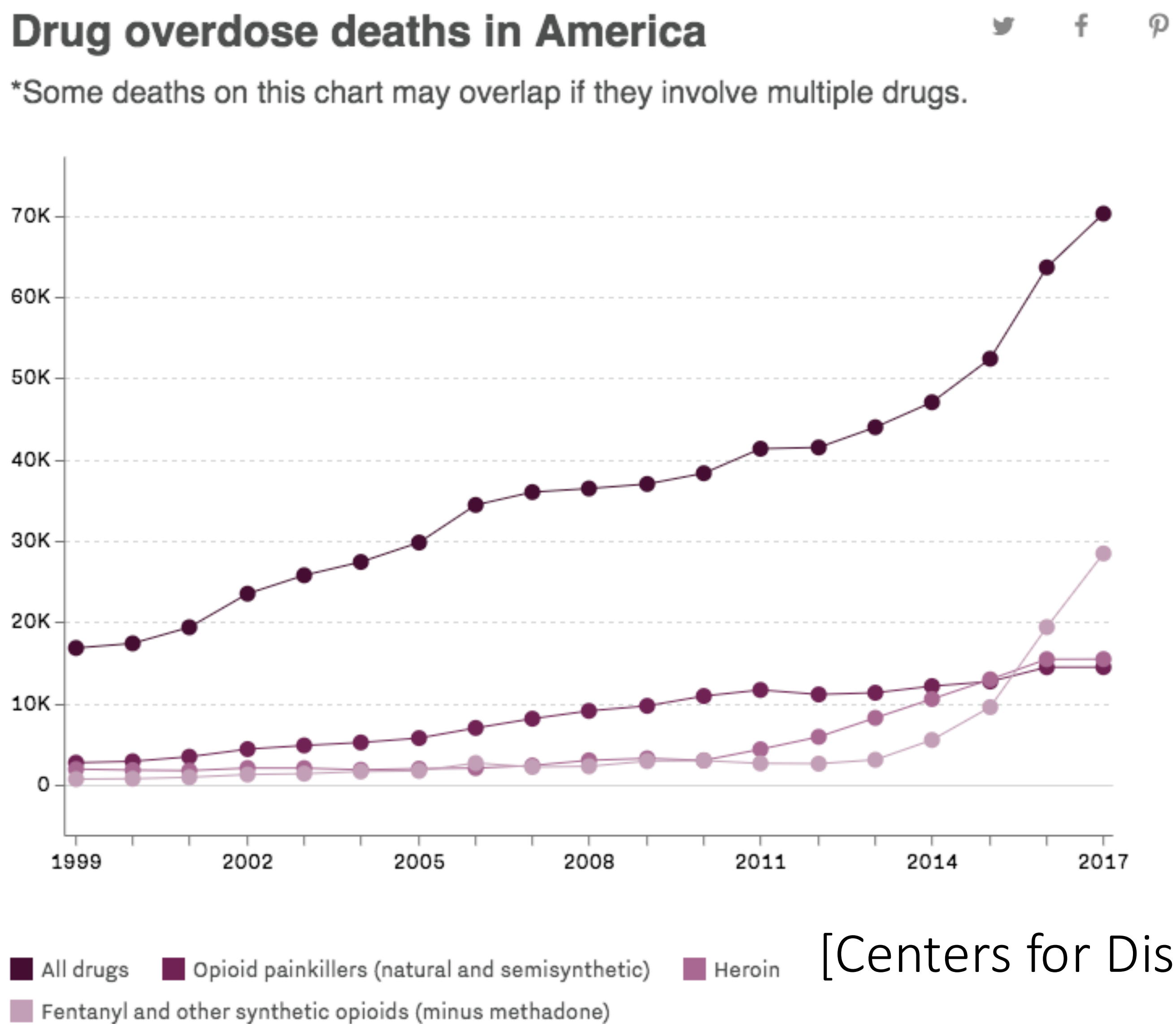
Causal Inference Case Studies

(adopted from Irene Chen, MIT)

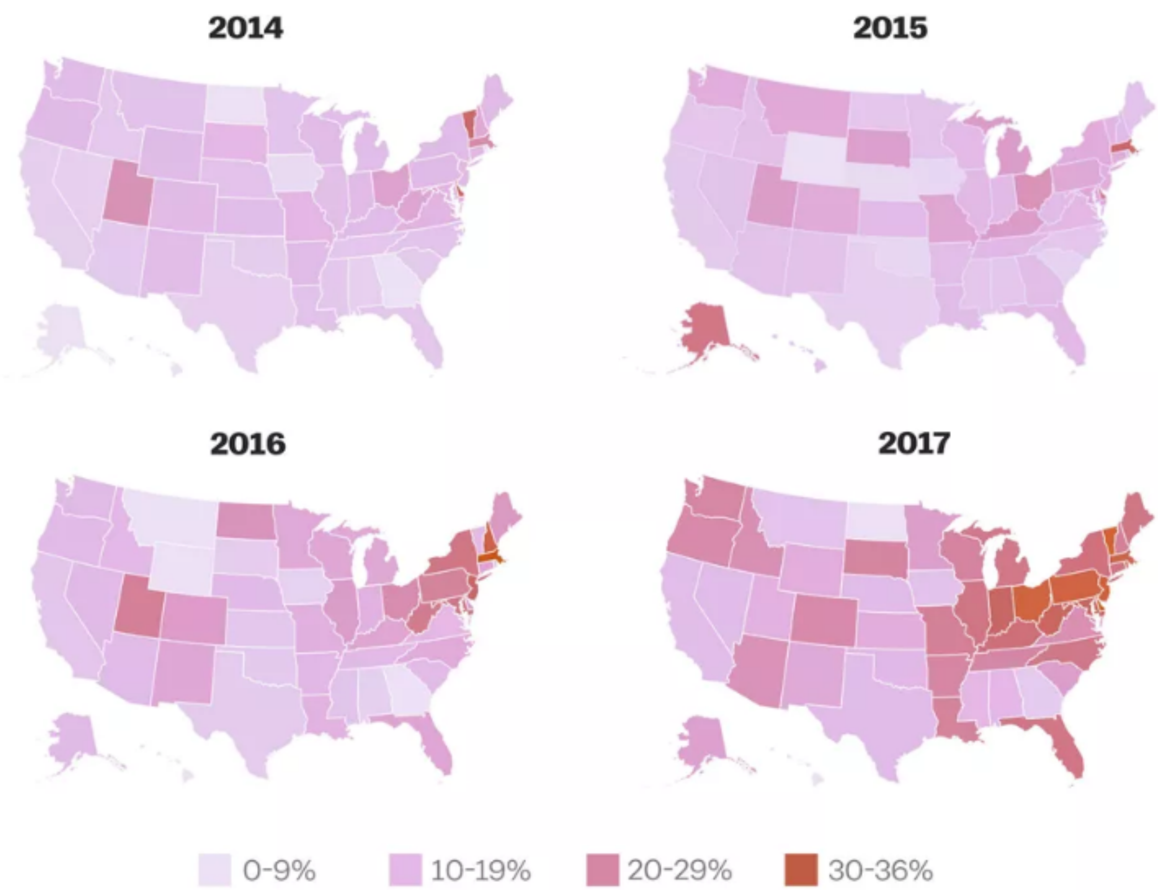
Case studies

1. **Post surgical opioid abuse**
2. Diabetes treatment management



[Centers for Disease Control]

Share of organ donors who died of drug overdoses



Source: Organ Procurement and Transplantation Network

Research

Postsurgical prescriptions for opioid naive patients and association with overdose and misuse: retrospective cohort study

BMJ 2018 ; 360 doi: https://doi.org/10.1136/bmj.j5790 (Published 17 January 2018)
Cite this as: *BMJ* 2018;360:j5790

Article | Related content | Metrics | Responses | Peer review

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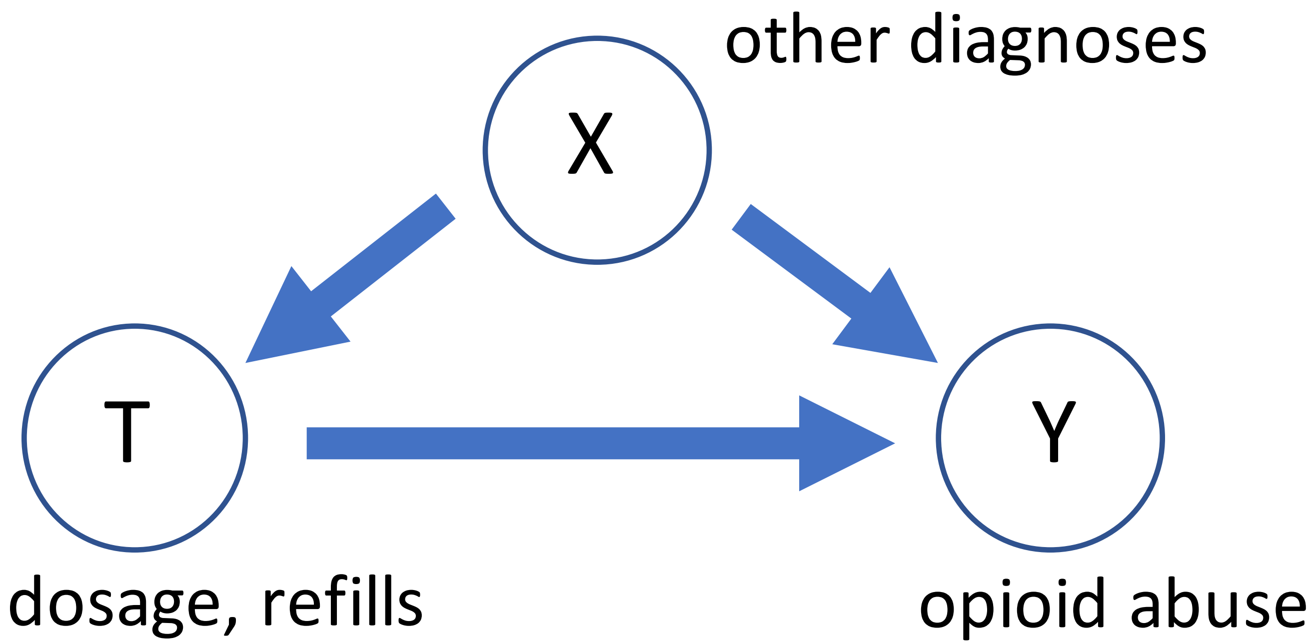
Do postsurgical opioids cause opioid abuse?



Aetna Insurance claims

Pros

- Complete patient record
- Hospital and pharmacy care
- Surgical claims from CPT, outcomes from ICD-9 codes

Cons

- Lacking granular information about hospital stays (e.g. lab values)
- CPT and ICD-9 codes can be incorrect or manipulated for billing purposes

Data source

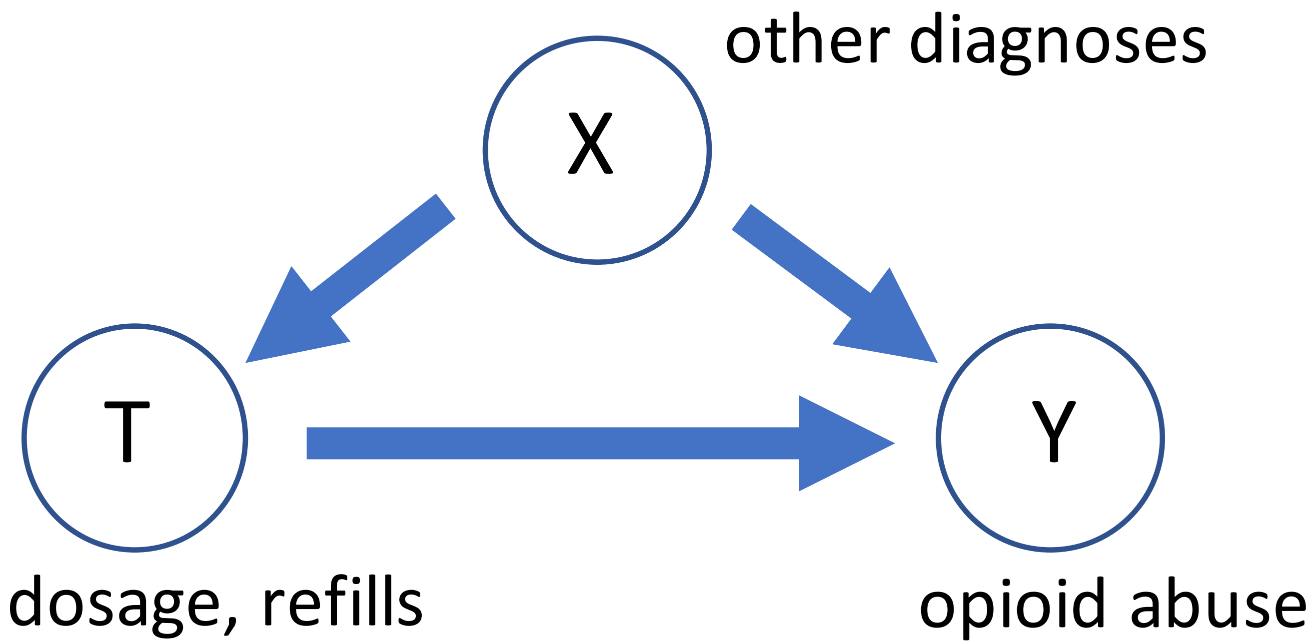
Include

- Patients with “complete” medical and pharmacy insurance records
- Underwent first surgery
- Opioid naïve: little/no previous opioid use

Final cohort

- Large dataset (37 million)
- Longitudinal (2008-2016)
- After inclusion criteria, 1 million opioid naïve patients undergoing surgery

Do postsurgical opioids cause opioid abuse?



How do we define T, Y, and X?

What is treatment T?

- Refill
- Total dosage
- Duration of use

What is outcome Y?

- ICD-9 code for opioid dependence, abuse, and overdose
- Only include diagnosis codes related to prescription opioids

What are confounders X?

- Demographics (age, sex)
- US state of residence
- surgery type group
- surgery year
- presurgical diagnoses

Statistical analysis

- Weighted linear regression for log transformed weekly rates of misuse
  - Each week weighted according to sample size
  - Create outcome of adjusted analysis of **time until misuse event** using Cox proportional hazards (survival analysis!)
  - Results report **multiplicative percentage increases** in rate
- Sensitivity analysis to rule out structural confounders
  - Interaction term between duration and year indicator
  - Interaction between duration and state of residence indicator
  - Build in an unobserved confounder with a Bernoulli random variable

Recap: Postsurgical opioid use to misuse

- "Duration more than dosage use may cause opioid misuse"
- Use covariate adjustment to estimate multiplicative effects
- Interaction terms

Case studies

1. Post surgical opioid abuse
2. **Diabetes treatment management**

Clinical Care/Education/Nutrition/Psychosocial Research

Personalized Diabetes Management Using Electronic Medical Records

Dimitris Bertsimas, Nathan Kallus, Alexander M. Weinstein and Ying Daisy Zhuo

+ Author Affiliations

Corresponding author: Dimitris Bertsimas, dbertsim@mit.edu.

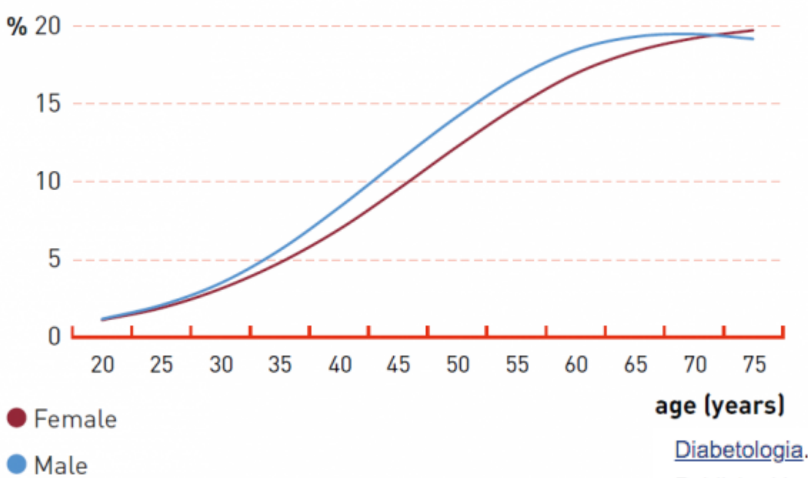
Diabetes Care 2017 Feb; 40(2): 210-217.
https://doi.org/10.2337/dc16-0826

Abstract

OBJECTIVE Current clinical guidelines for managing type 2 diabetes do not differentiate based on patient-specific factors. We present a data-driven algorithm for personalized diabetes management that improves health outcomes relative to the standard of care.

Type 2 Diabetes Treatment Still a Mystery

Figure 2.2 **Prevalence (%) of people with diabetes by age and sex, 2013**



BMJ Open. 2015; 5(5): e007375. PMCID: PMC4431069
Published online 2015 May 12. doi: 10.1136/bmjopen-2014-007375 PMID: 25967997

Racial ethnic differences in type 2 diabetes treatment patterns and glycaemic control in the Boston Area Community Health Survey

Sunali D Goonesekera, May H Yang, Susan A Hall, Shona C Fang, Rebecca S Piccolo, and John B McKinlay

‣ Author information ‣ Article notes ‣ Copyright and License information Disclaimer

Diabetologia. Author manuscript; available in PMC 2014 Dec 1. PMCID: PMC3842214
Published in final edited form as: NIHMSID: NIHMS529351
Diabetologia. 2013 Dec; 56(12): 10.1007/s00125-013-3078-7. PMID: 24092493
Published online 2013 Oct 5. doi: 10.1007/s00125-013-3078-7

Age-related differences in glycaemic control in diabetes

Elizabeth Selvin[1] and Christina M. Parrinello[1]

What do we include in this analysis?

Inclusion criteria

- Patients in hospital EMR for >1 year
- Prescription for at least one blood glucose regulation agent
- At least three recorded laboratory results for HbA1C
- No recorded diagnosis of type 1 diabetes (from ICD-9 code 250.x1 or 250.x3)

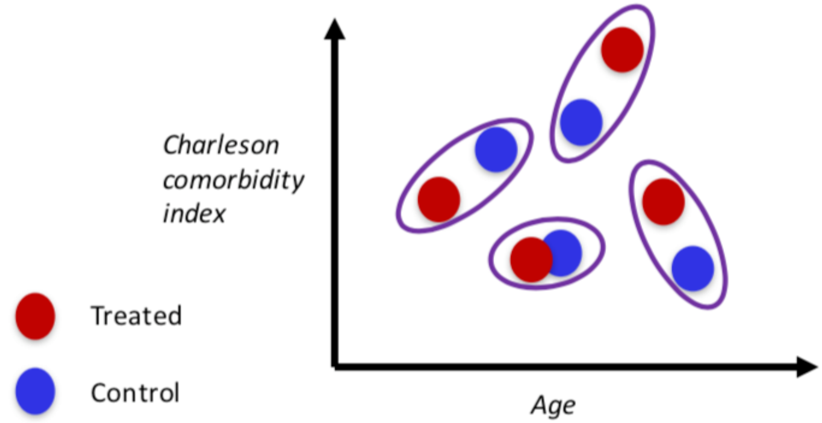
Final cohort

- 10k patients, 48k patient visits
- Access to demographic information
- Analyze all associated EMR data

What makes two patients similar or different?

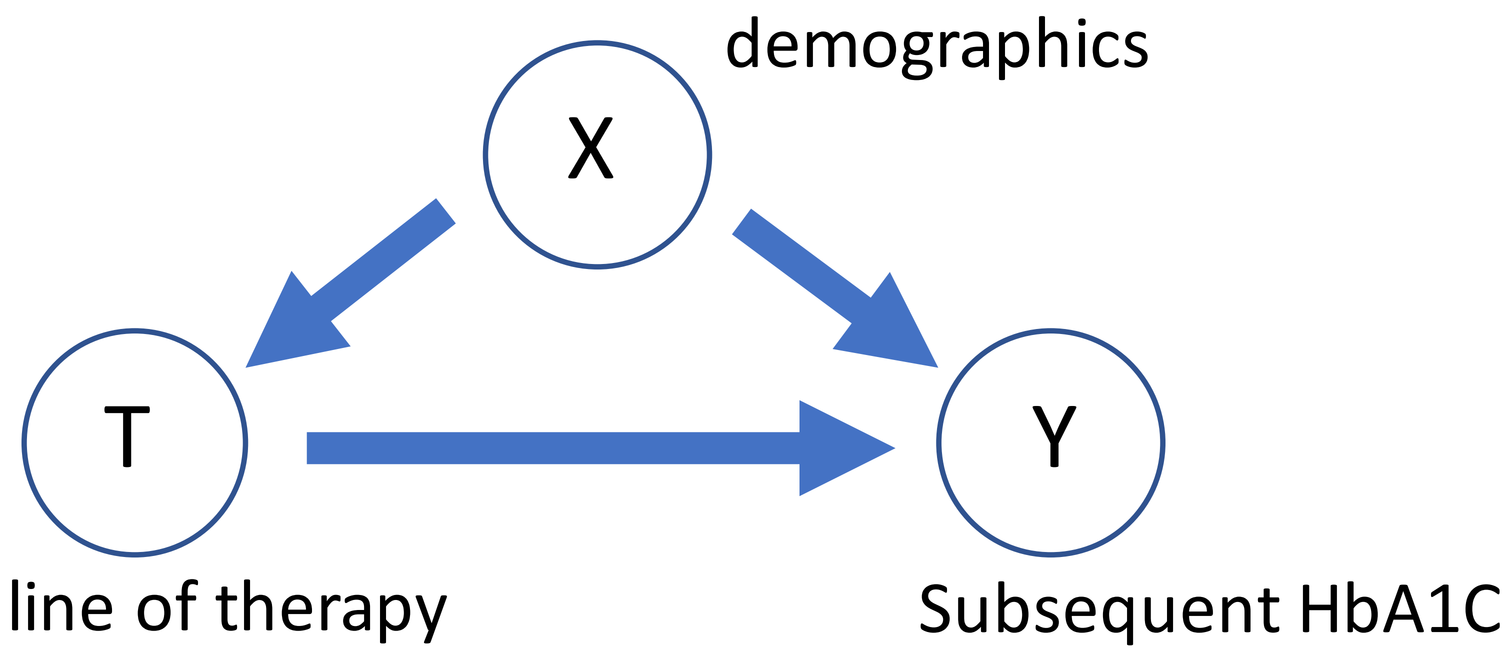
Features

- Differentiate 13 lines of therapy
- Patient visit every 100 day and average HbA1C after visit (75-200 days after)
- Collect what standard of care was actually administered



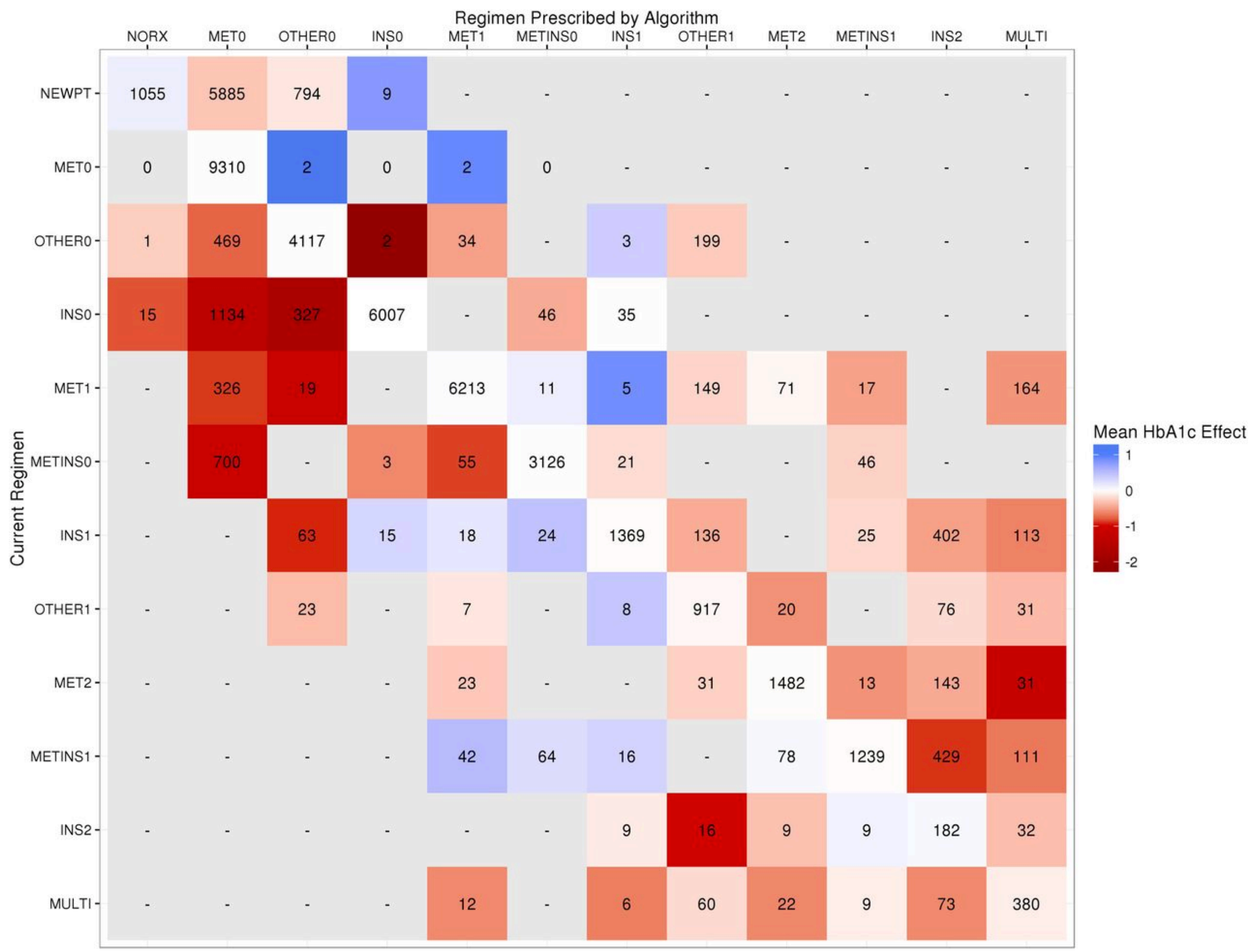
[Slide 17 of lecture 15]

Which treatment will lead to lower HbA1C?

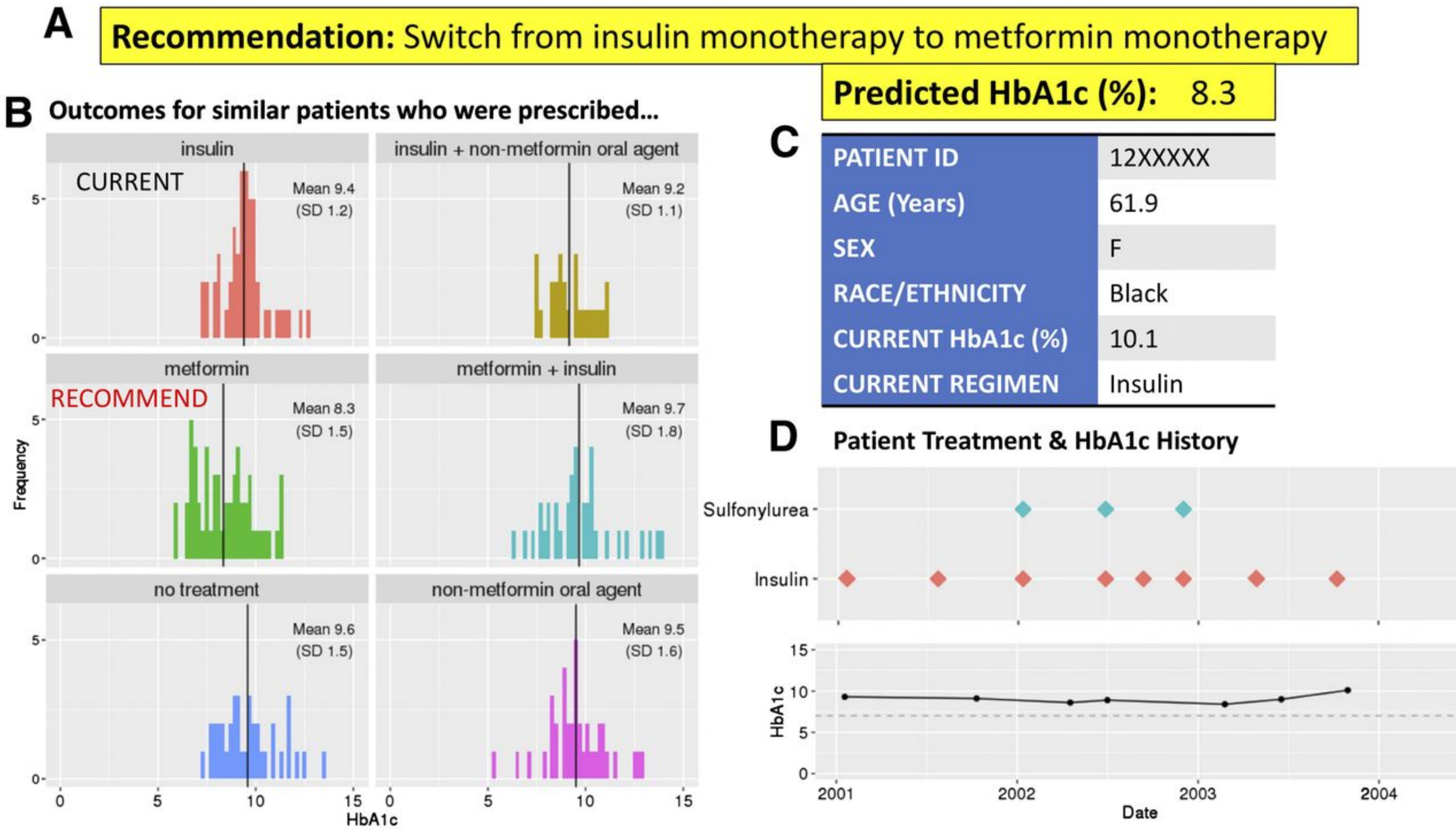


Model

- For each patient visit, find kNN regression to predict HbA1C under every possible treatment
- Algorithm prescribes regimen with best predicted outcome if predictive improvement exceeds threshold
- Evaluation compared actual treatment and outcome with recommended therapy and outcome
- Sensitivity analysis by drawing new training and testing splits



[Figure 1 of Bertsimas et al, 2017]



[Figure 2 of Bertsimas et al, 2017]

Recap: Diabetes treatment management

- “kNN over patients can recommend diabetes treatments”
- Use matching to estimate different treatment effects
- Evaluate by comparing predicted and actual treatment and HbA1C values
- Sensitivity analysis through repeated sampling of training and test data