Machine learning models of addiction treatment outcomes: An exploratory analysis

Abby Stevens
& Harold Pollack

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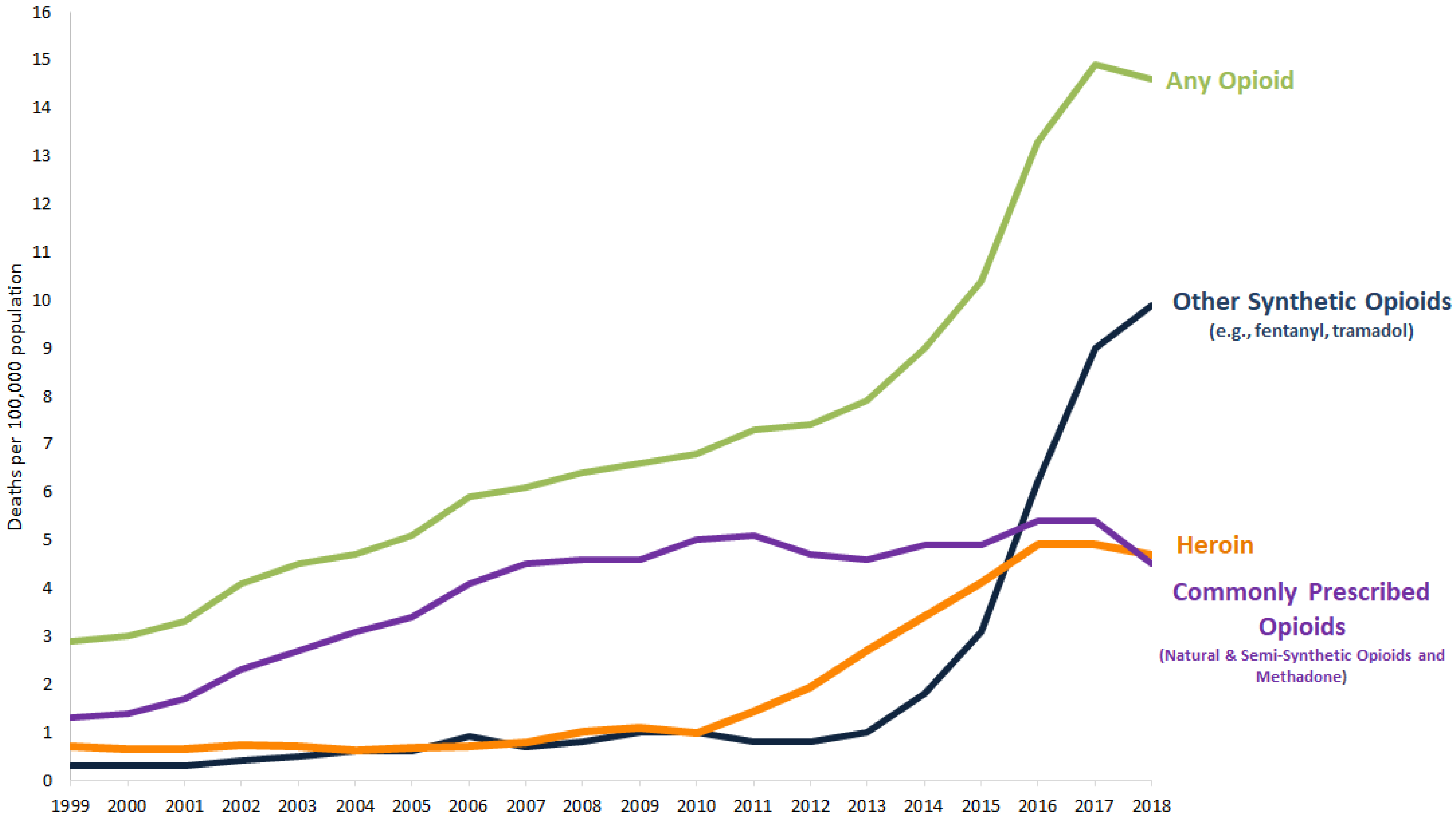
Background and significance

- More Americans will likely die of drug overdose than will die from COVID-19 over the course of the Biden administration.
- Substance use disorder treatment--particularly medication opioid use disorder treatment (MOUD)--is a key, albeit imperfect tool to reduce mortality and morbidity associated with substance use.
- Identifying SUD patients likely to experience unfavorable treatment outcomes may
  - Inform the allocation of harm reduction efforts (e.g. naloxone) to specific subgroups at risk.
  - Generate hypotheses for improved service delivery through provision of complementary or focused resources.
  - Identified features may inform hypotheses or identify specific subgroups for future study designs that inform causal inference.
  - Analyses may inform changing treatment patterns and outcomes over time.
- A growing literature identifies patterns (e.g. poly-substance use) associated with fatal overdose. Less well-known is whether and how these patterns may be associated with adverse treatment outcomes.

Overdose Death Rates Involving Opioids, by Type, United States, 1999-2018

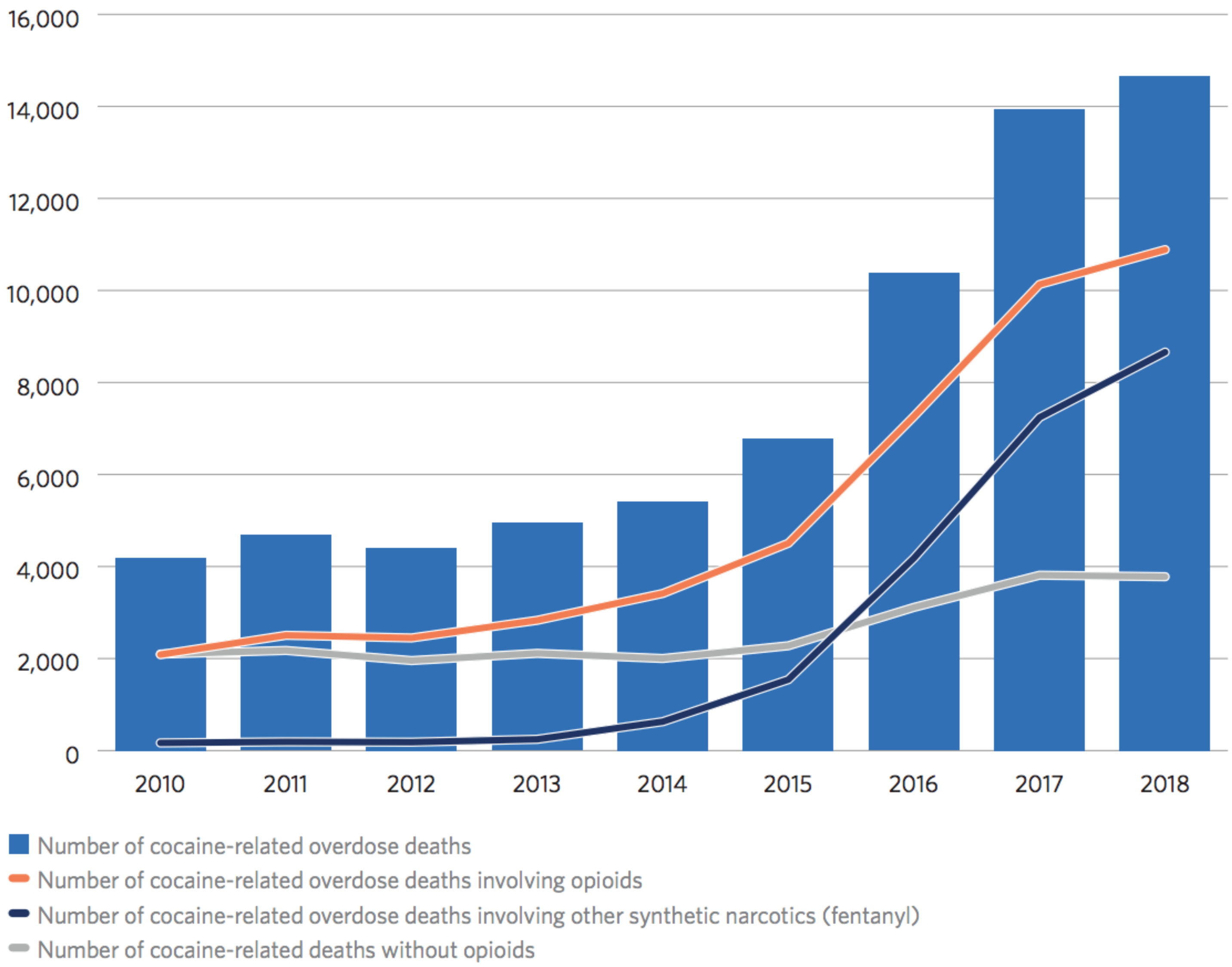


SOURCE: CDC/NCHS, National Vital Statistics System, Mortality. CDC WONDER, Atlanta, GA: US Department of Health and Human Services, CDC; 2020. https://wonder.cdc.gov/.

www.cdc.gov
Your Source for Credible Health Information

Figure 2

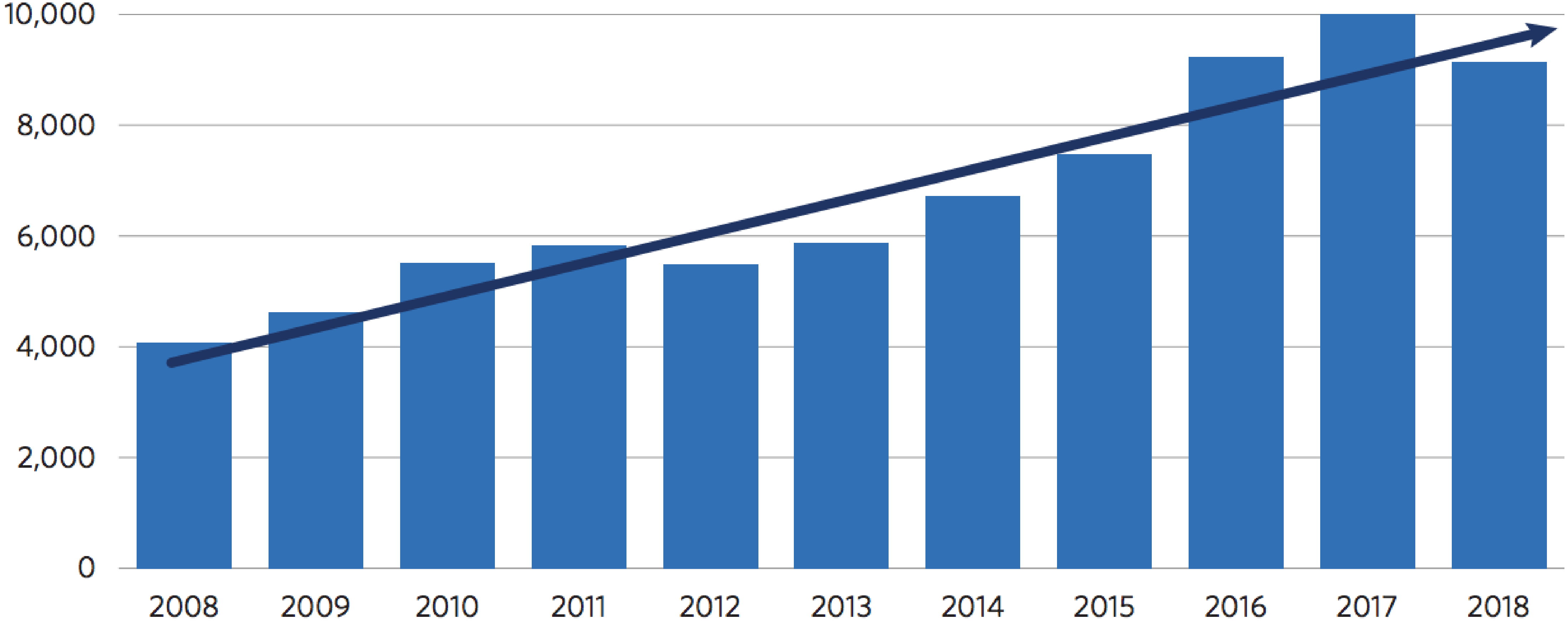
Opioids Involved in Cocaine-Related Overdose Deaths, 2010-2018



Source: CDC Wonder

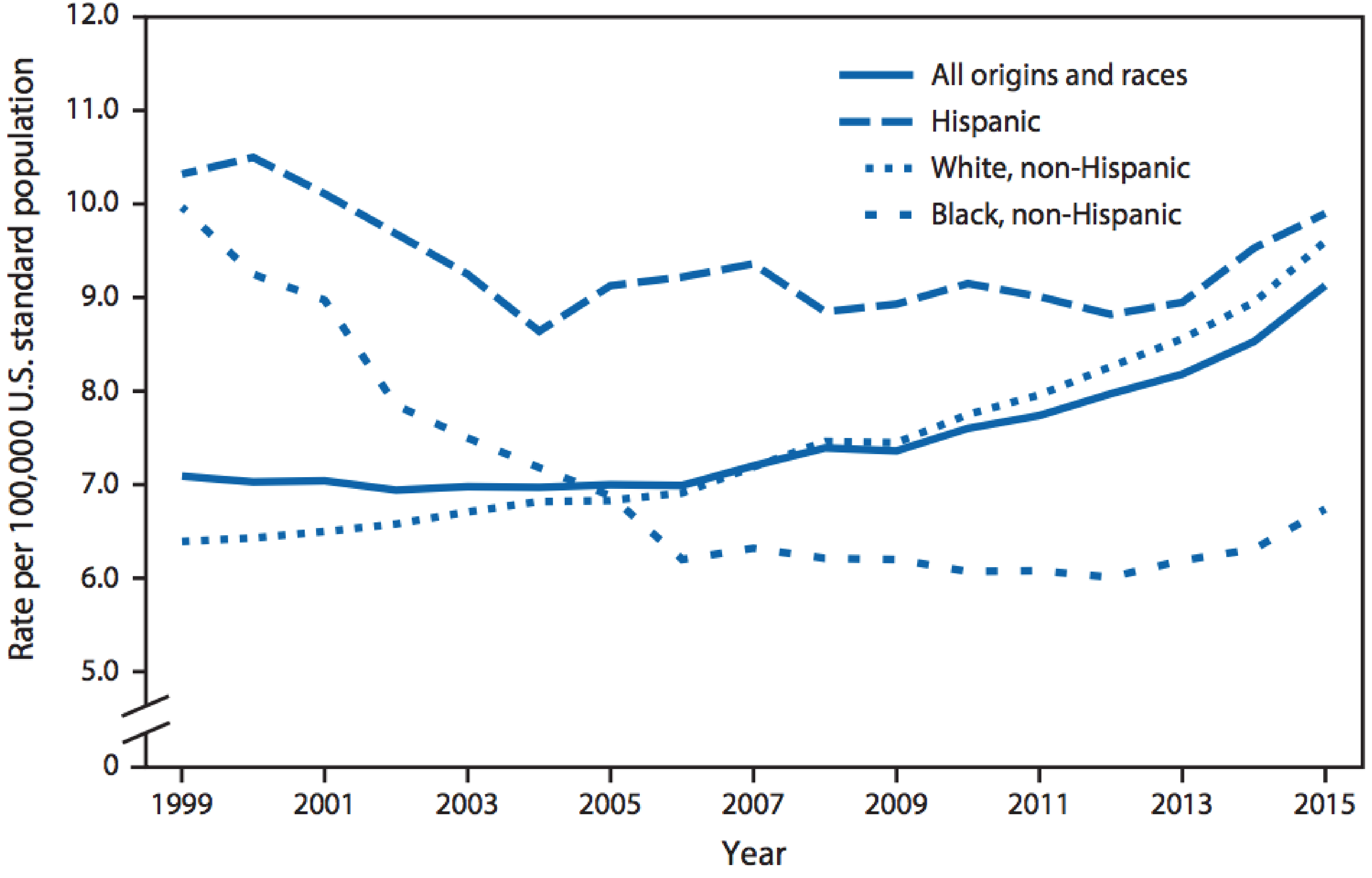
Figure 1

Overdose Deaths Involving Benzodiazepines and Opioids, 2008-2018



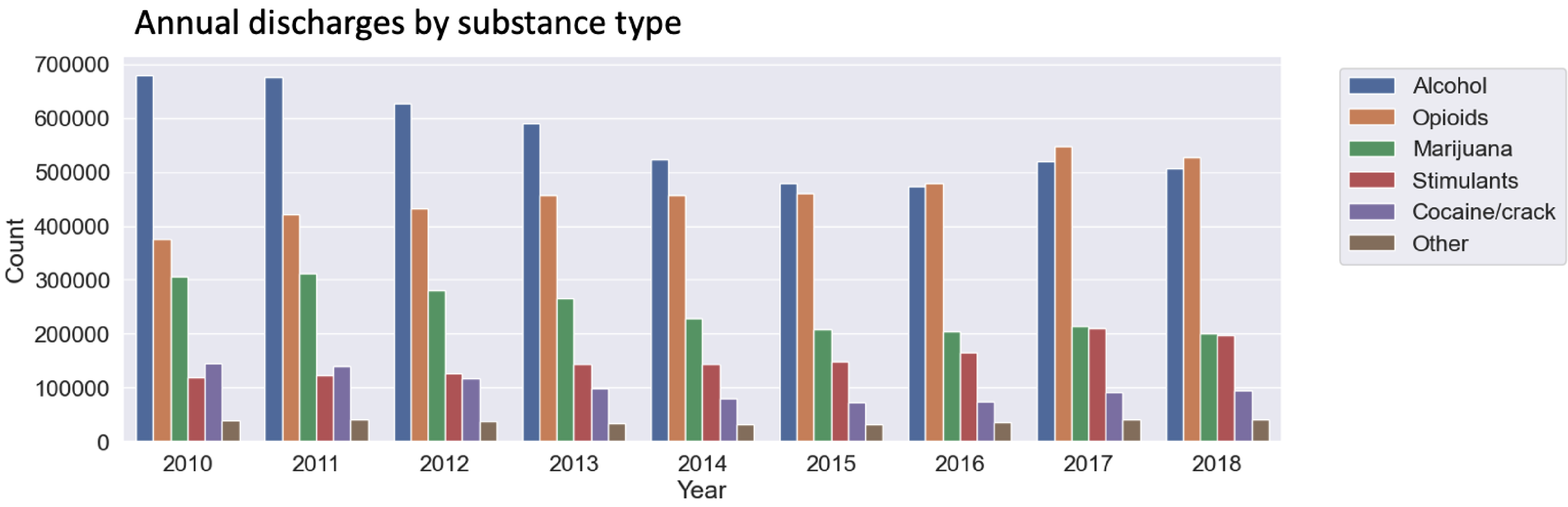
Source: CDC Wonder

Age-Adjusted Death Rates* Attributable to Alcohol-Induced Causes,† by Race/Ethnicity — United States, 1999–2015

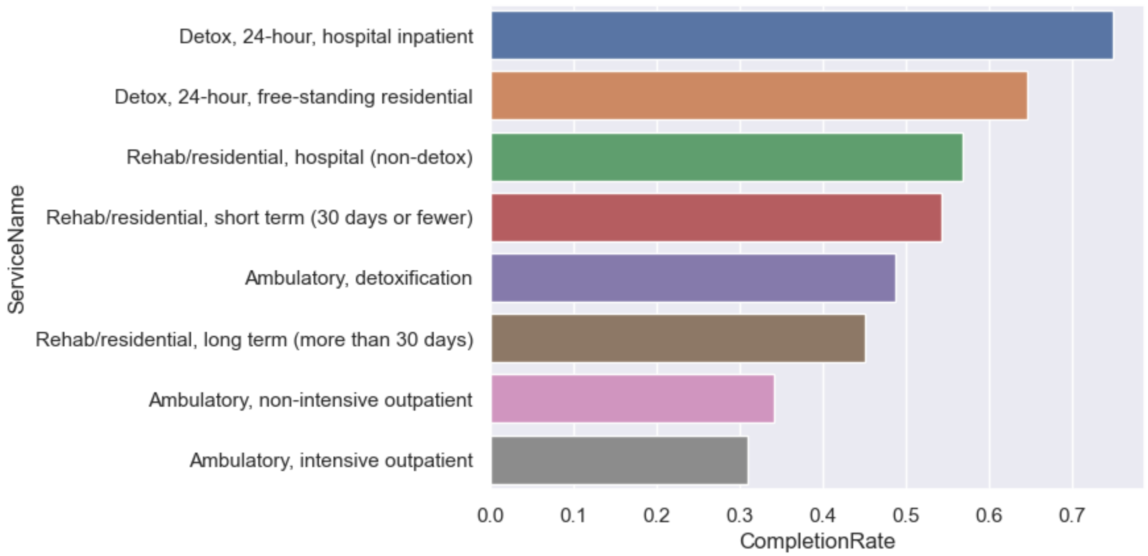


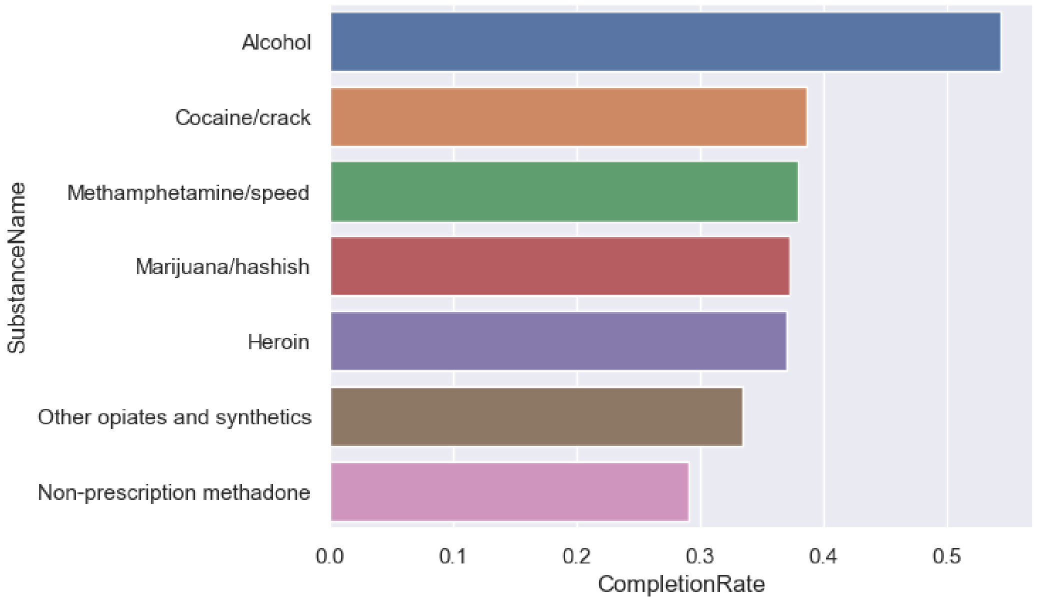
Treatment Episode Data Set (TEDS)

- National data system of annual admissions/discharges from substance use disorder treatment facilities.
- Includes facilities that report to individual state administrative data systems

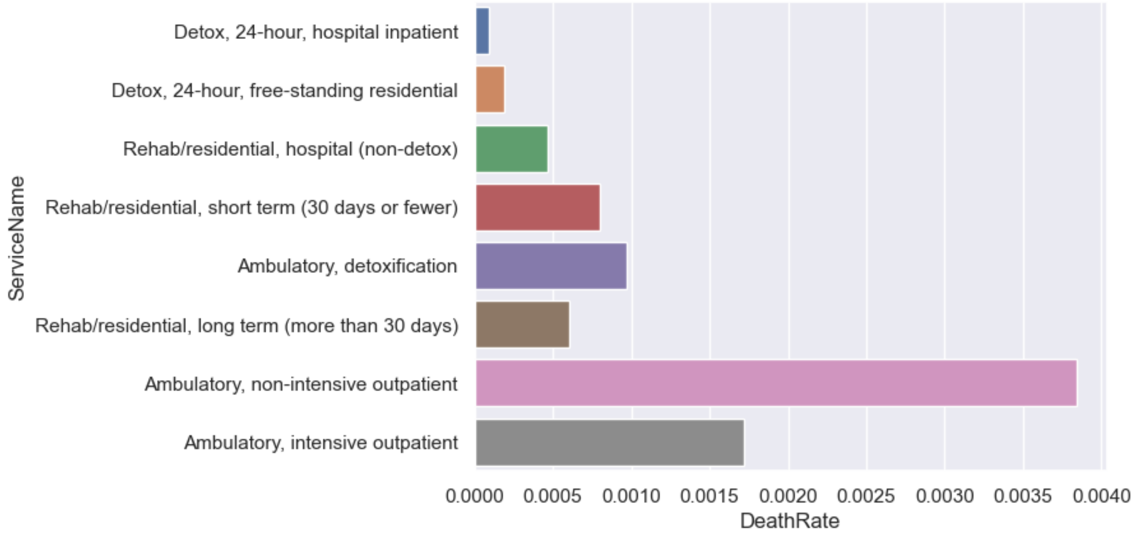


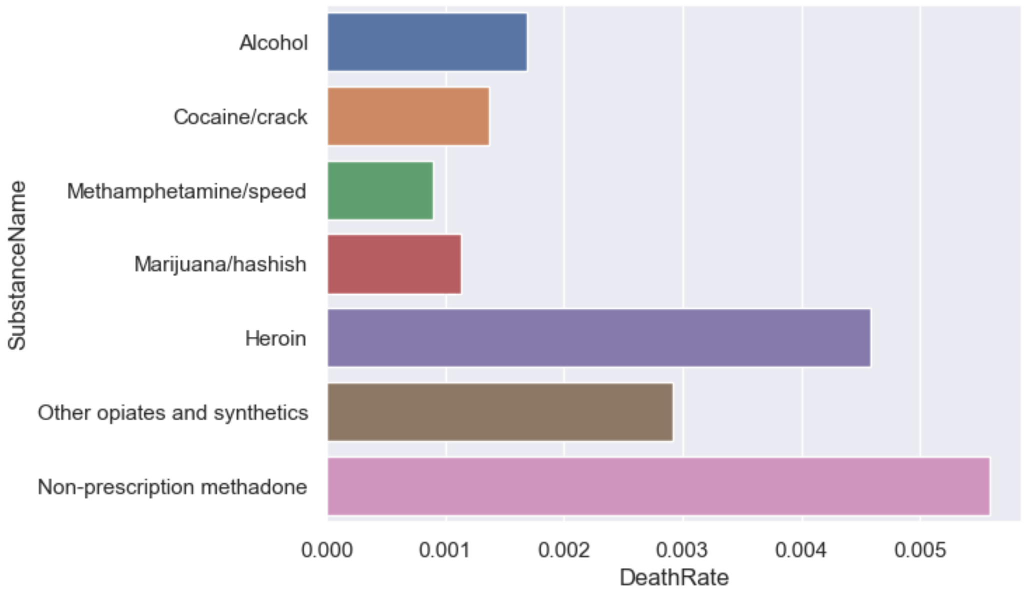
"Successful" treatment completion



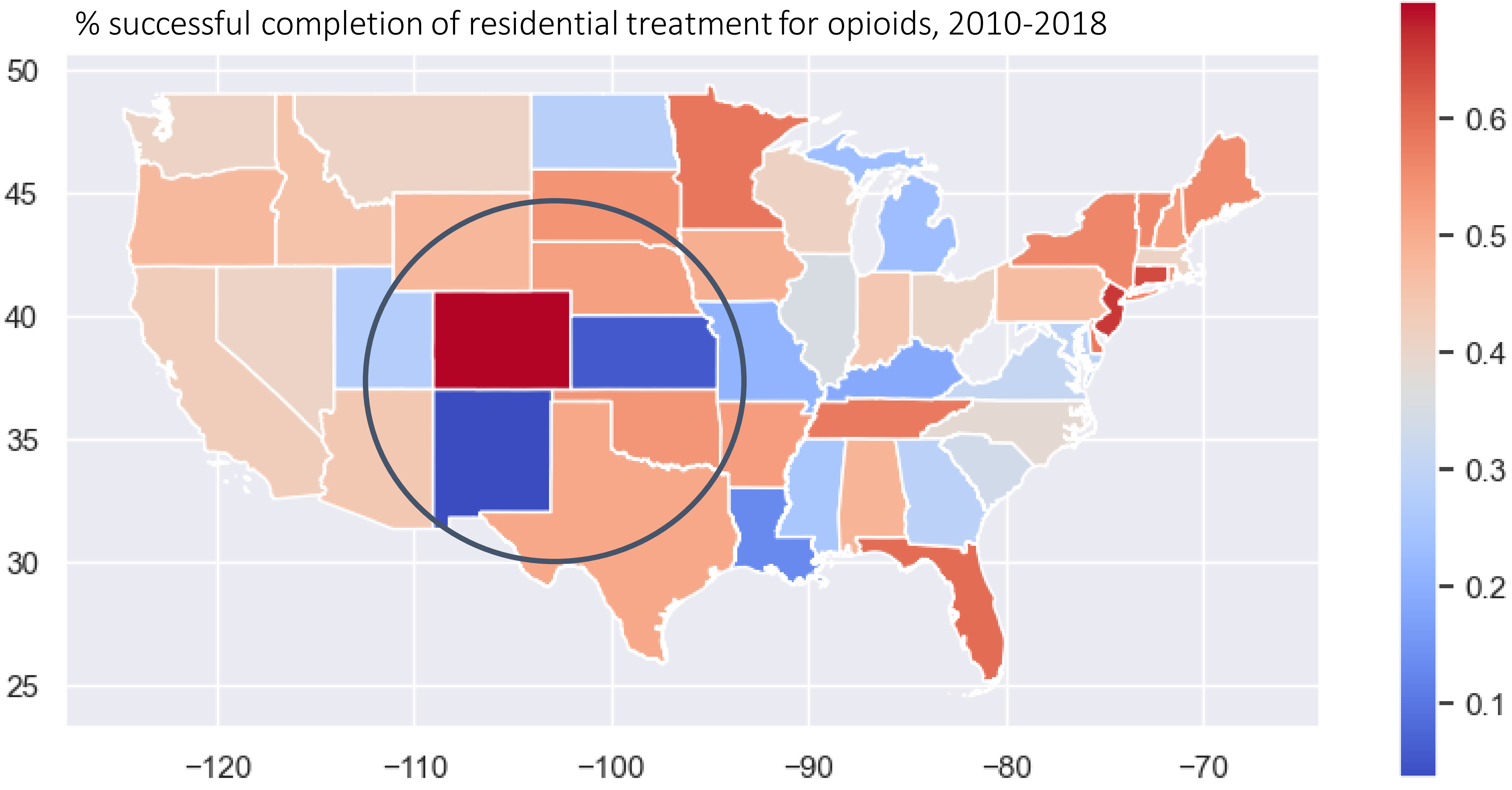


Deaths during treatment

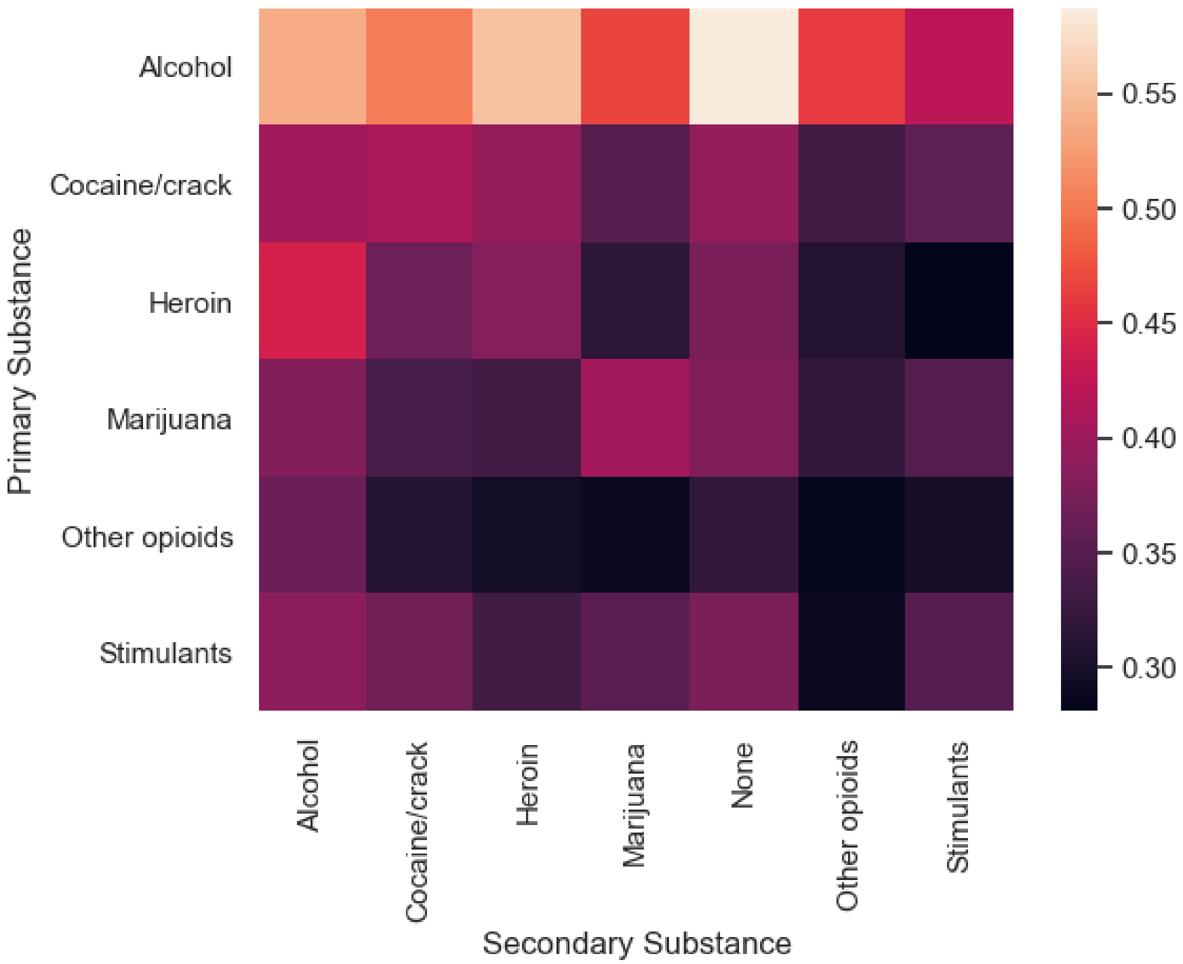




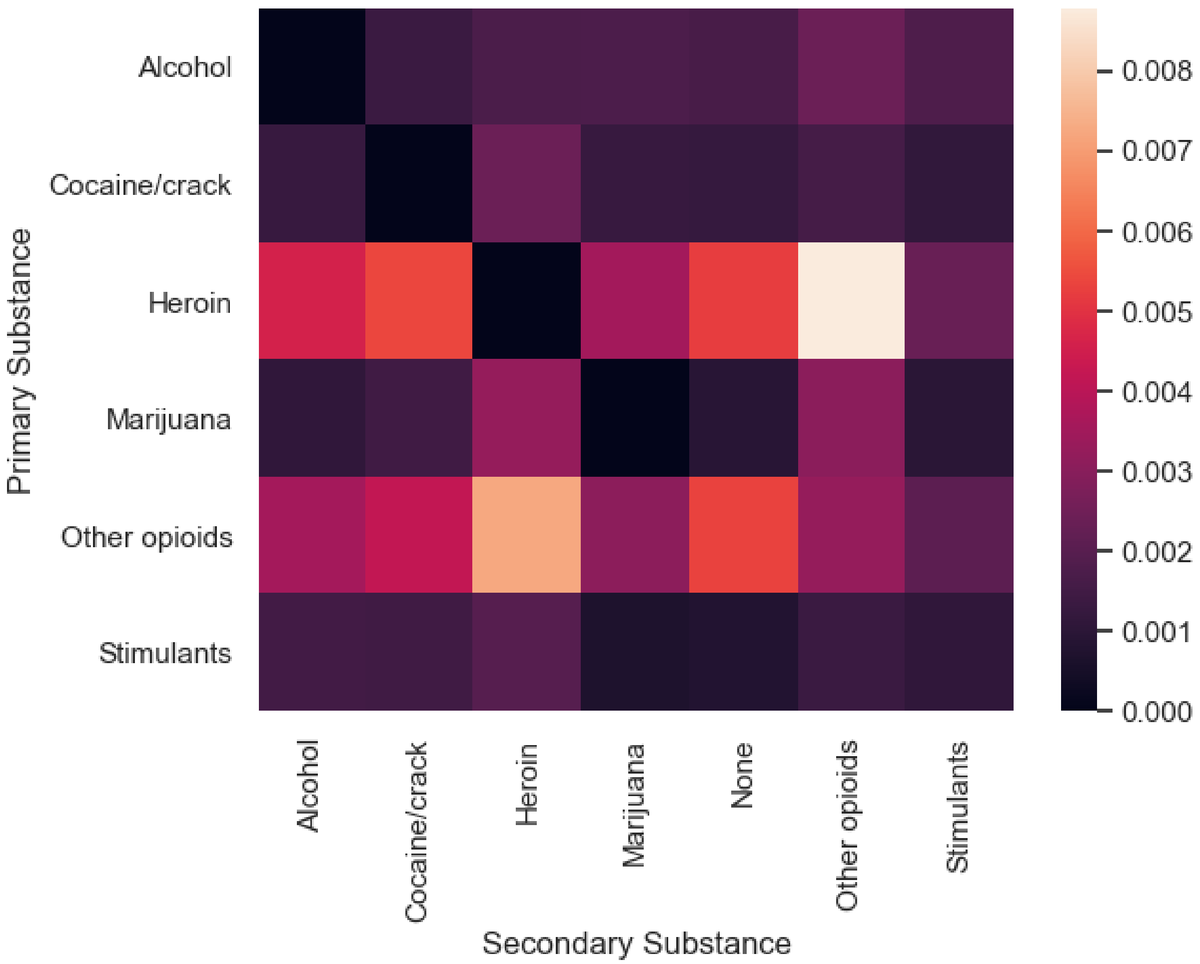
% successful completion of residential treatment for opioids, 2010-2018



Completion rate across all treatments by primary/secondary substance



Death rate across all treatments by primary/secondary substance



Predicting treatment outcomes

Understanding who is succeeding in treatment helps direct resources to those who aren’t.

Binary classification: $y_i \in \{0,1\}$, $X_i = \{$demographics, other substances, payment info, etc.$\}$

Design decisions influence outcomes (e.g. handling missing data)

Goal: Classify unseen sample y_j given X_j

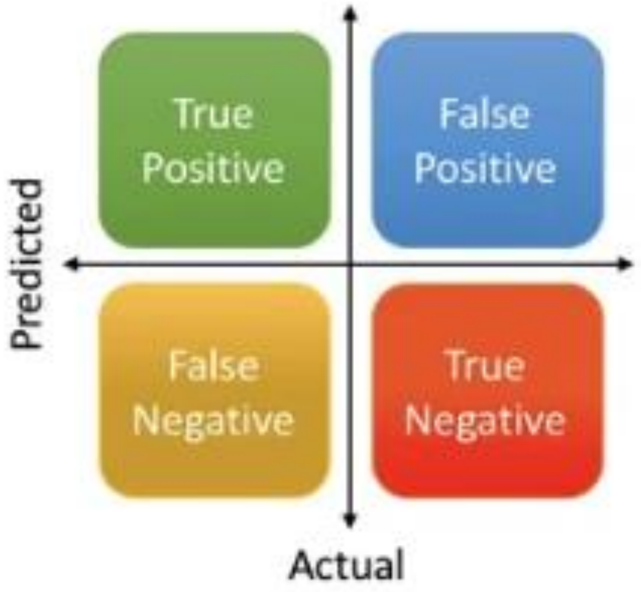
Training data (75%)

Test

Evaluate performance

Evaluation metrics

$$\textbf{Accuracy} = \frac{\text{True Positive} + \text{True Negative}}{\text{Total}}$$



$$\textbf{Precision (PPV)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Positive}}$$

Of what the **model labeled positive**, how many were right? Precision is important when one wants to allocate scarce resources to those with this particular label.

$$\textbf{Recall (sensitivity)} = \frac{\text{True Positive}}{\text{True Positive} + \text{False Negative}}$$

Of actual **positive** samples**,** how many were correctly identified?

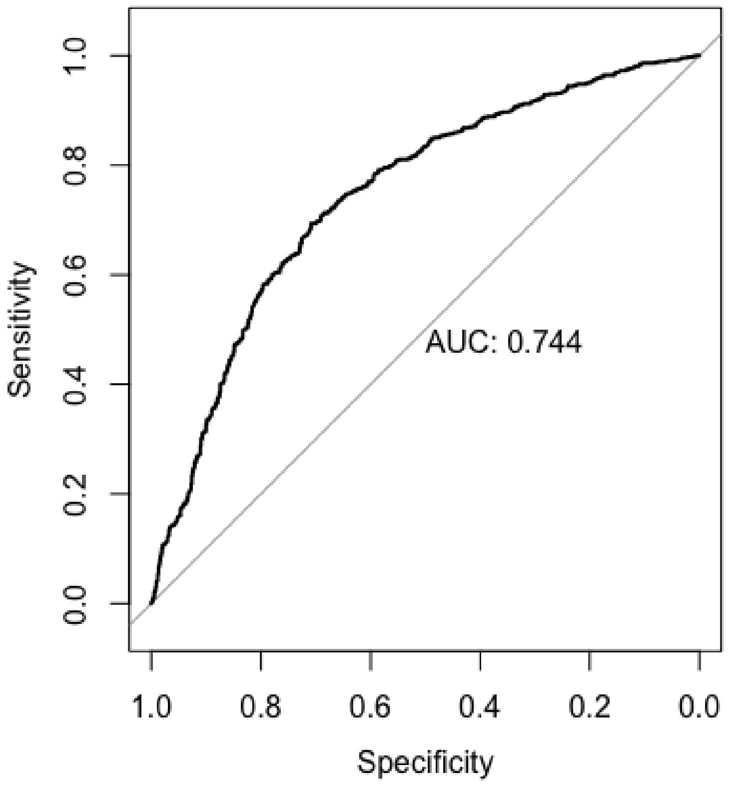
$$\textbf{Specificity} = \frac{\text{True Negative}}{\text{True Negative} + \text{False Positive}}$$

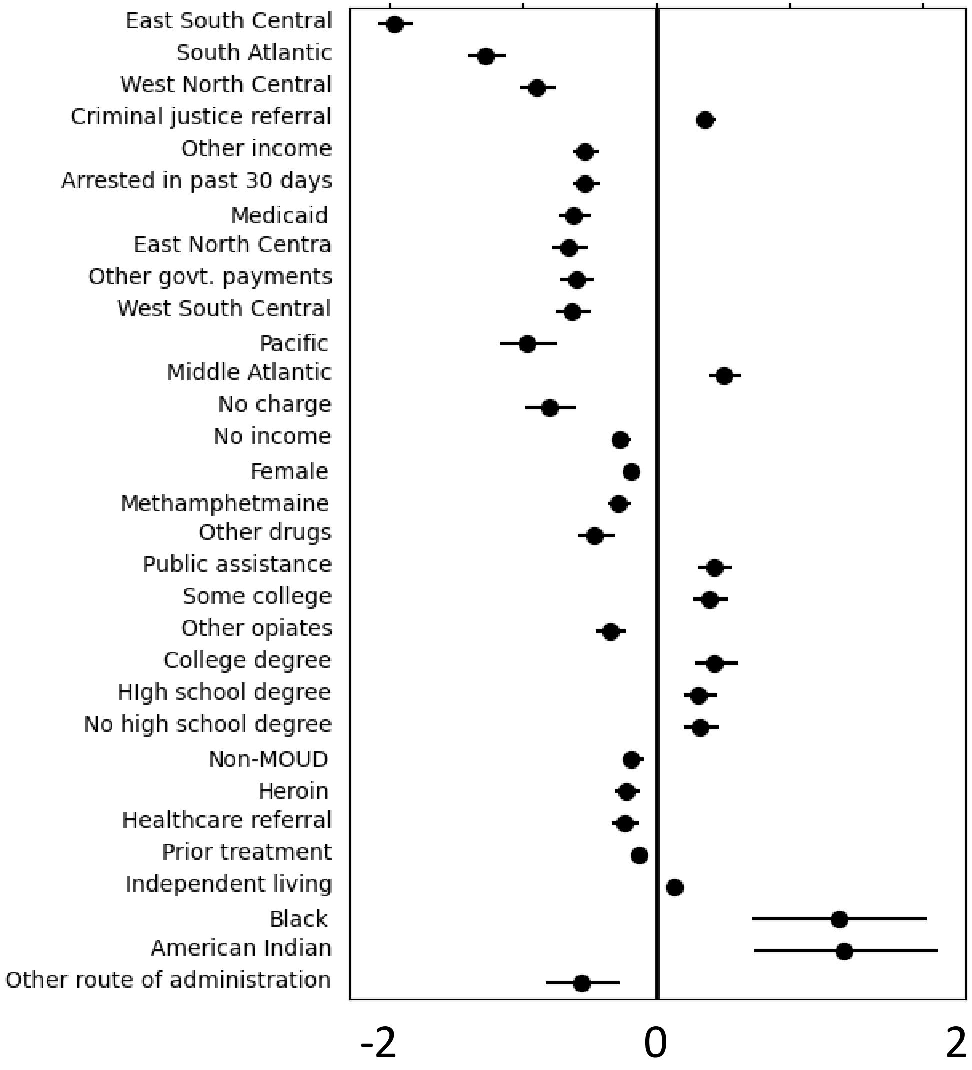
Of actual **negative** samples**,** how many were correctly identified?

Logistic Regression

Year: 2018
Substance: Opioids
Treatment: Residential rehab
Response: Treatment completion

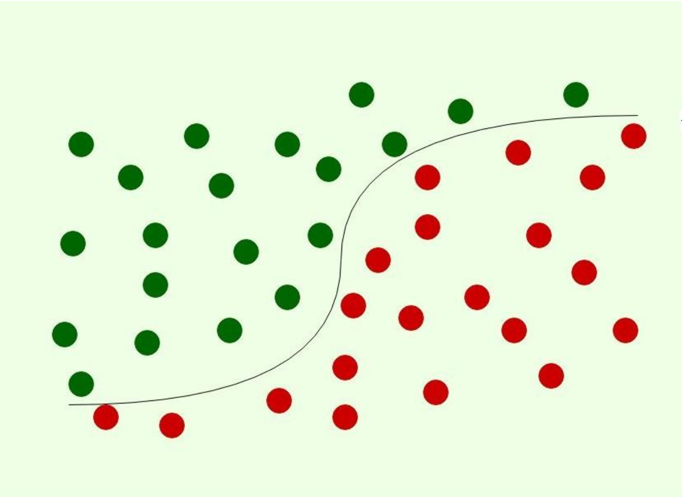
$$\log\frac{p}{1-p} = \beta_0 + \beta_1 x_1 + \ \ldots + \beta_p x$$

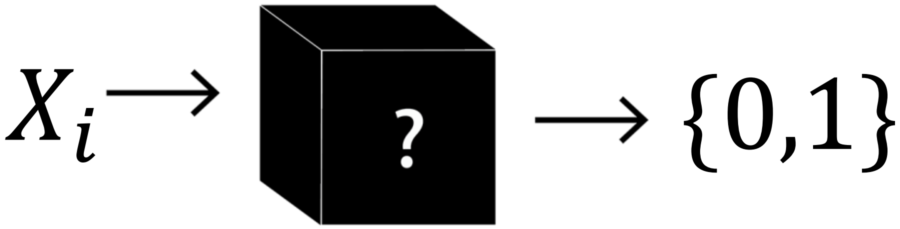




Estimated coefficients and standard errors

Logistic Regression vs. ”Machine Learning”





Linear model with interpretable coefficients

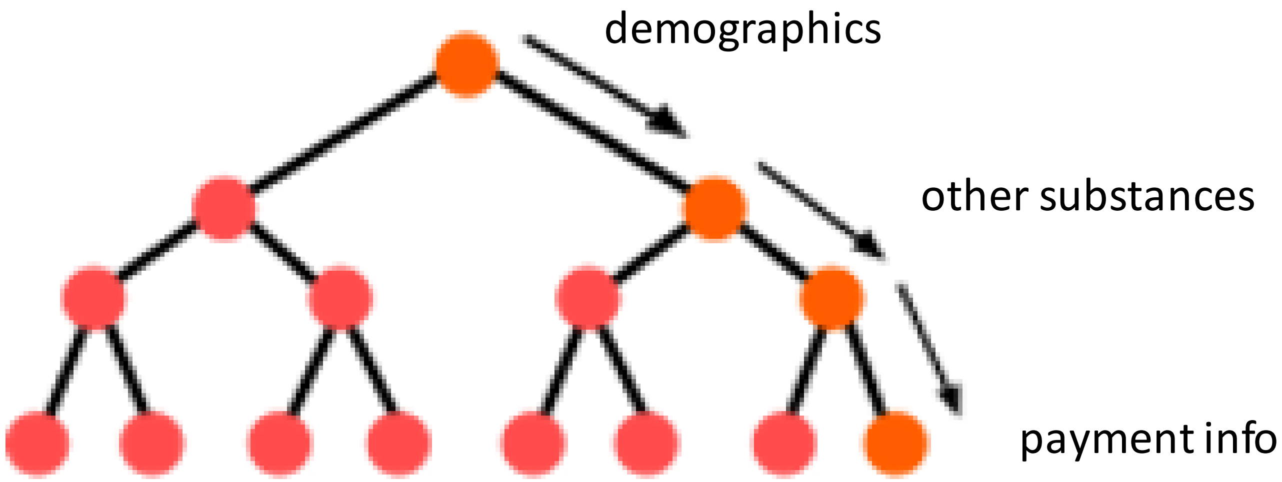
Optimizes for **interpretability**

“Black box”

Optimizes for **predictability**

Decision Tree Classifier

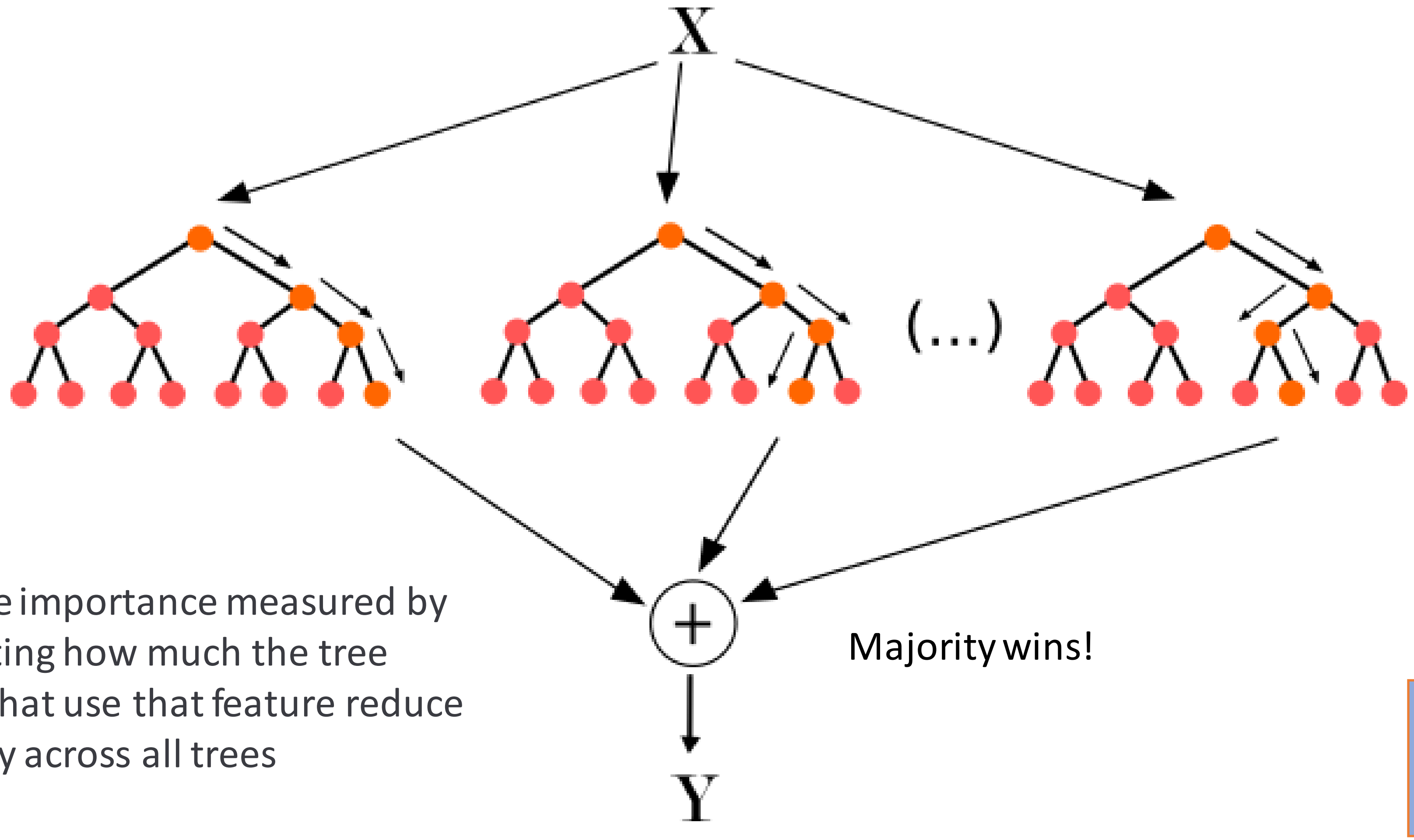
X_i = {demographics, other substances, payment info, etc.}



Split the data on the feature that results in the **largest information gain**

Tend to **overfit** the training data

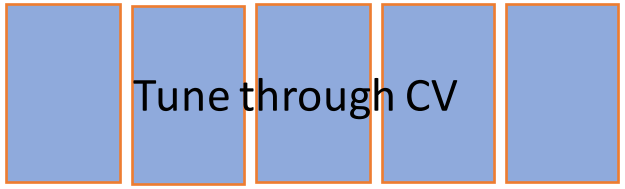
Random Forest Classifier



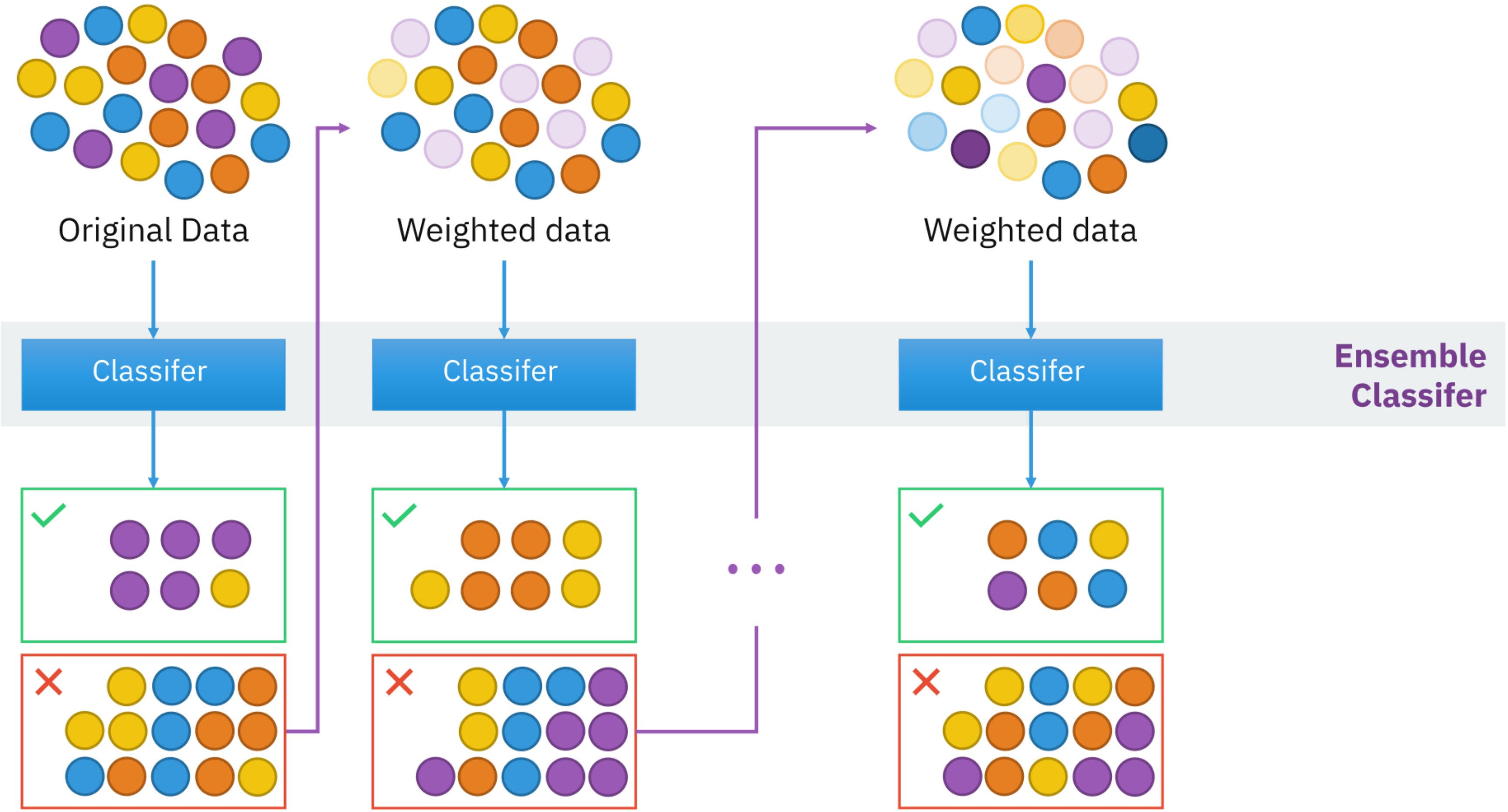
Each node splits on a **random subset of features**

Variable importance measured by computing how much the tree nodes that use that feature reduce impurity across all trees

Majority wins!

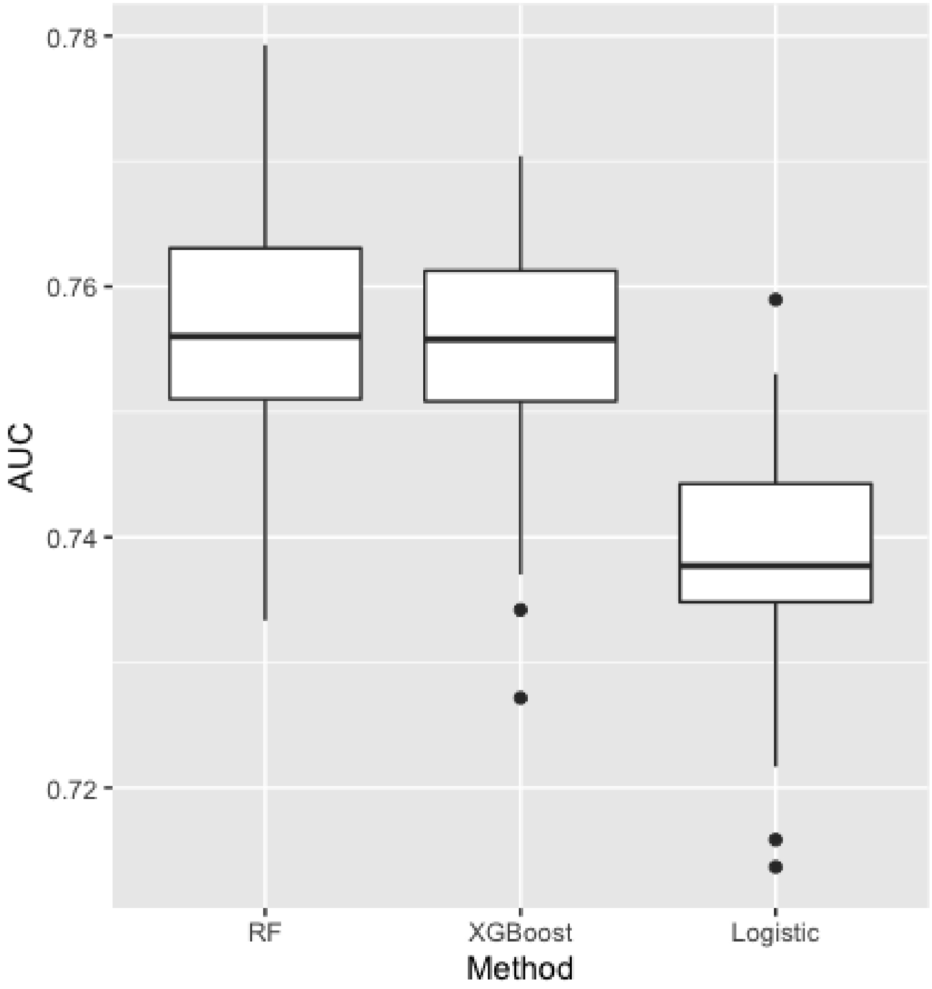


Beyond Random Forests - Boosting



Year: 2018
Substance: Opioids
Treatment: Residential rehab
Response: Treatment completion

Predictive boost

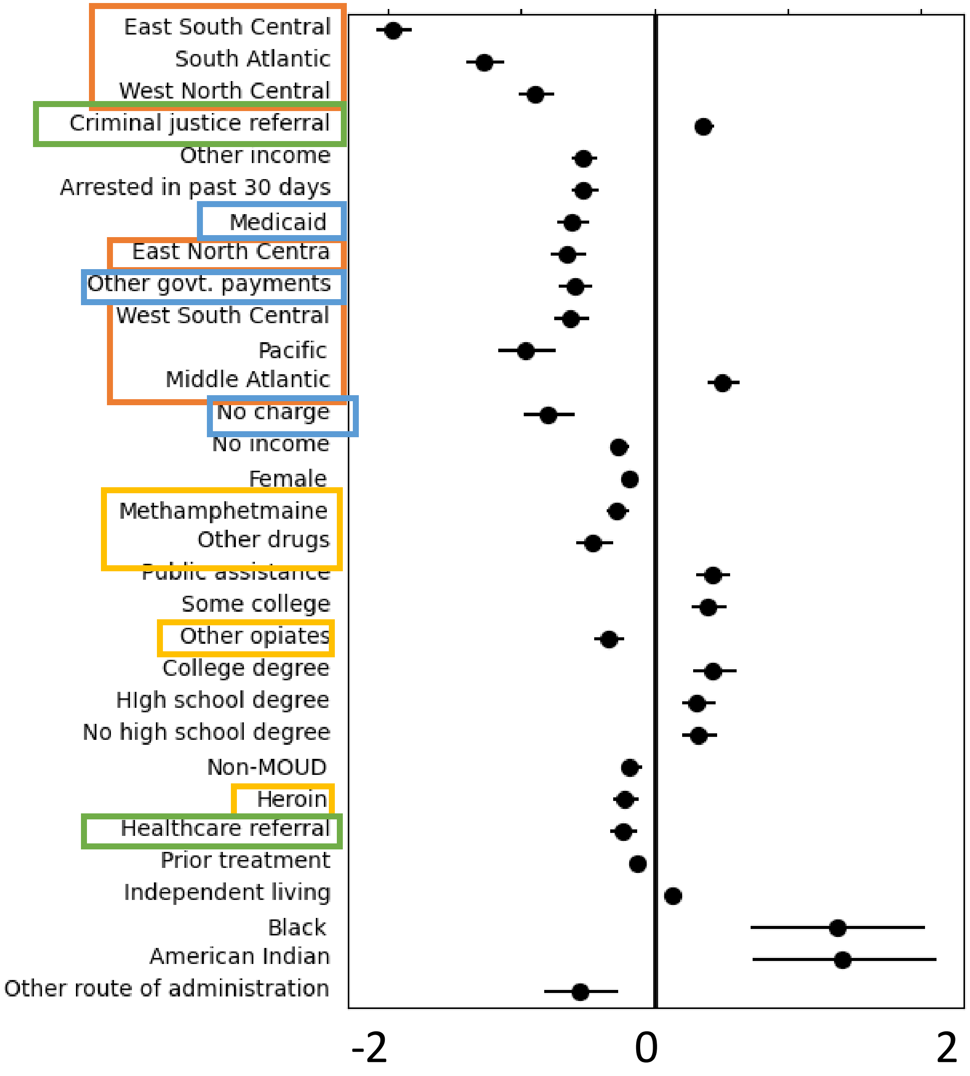


- ML methods optimized for better prediction
- Predictive boost consistent but not drastic
- ML framework allows for focus on outcomes, imperative for resource allocation

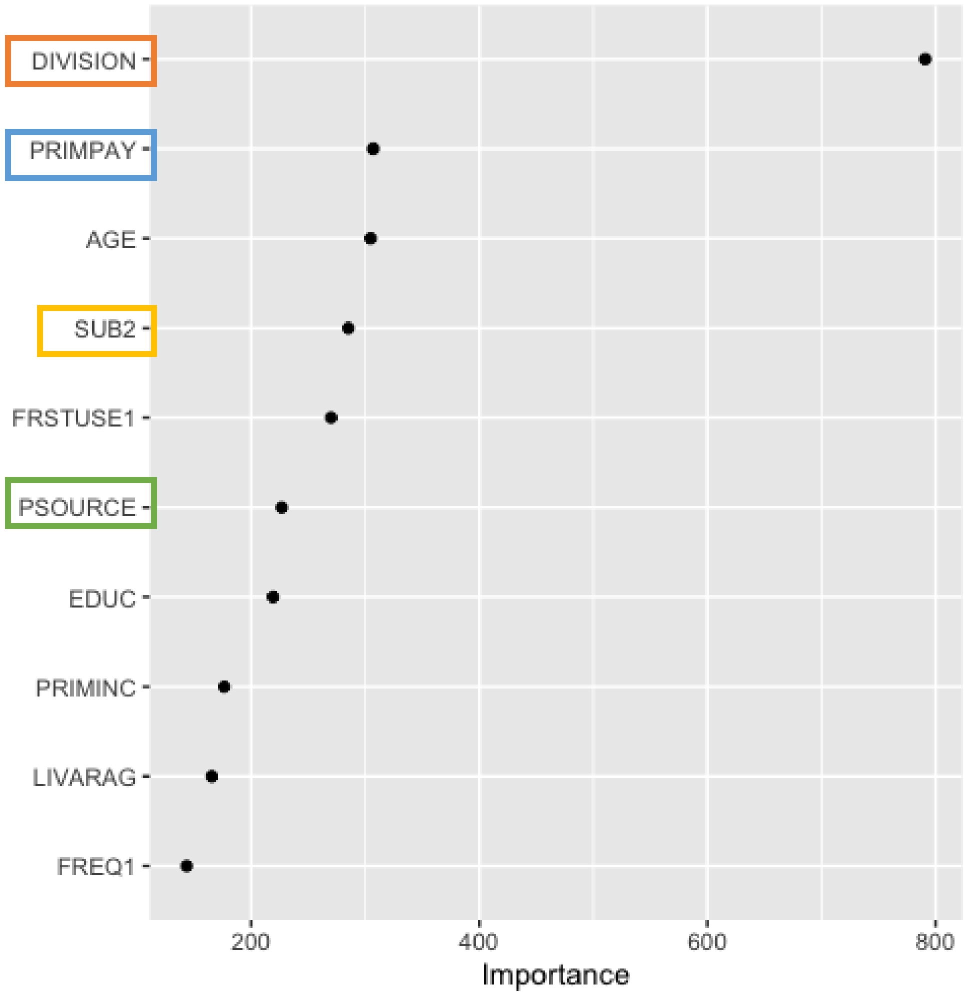
Are they interpretable?

Year: 2018
Substance: Opioids
Treatment: Residential rehab
Response: Treatment completion

Coefficients from Logistic regression



Random Forest variable importance



Substantive questions to answer with TEDS

- How do predictability and emergent predictors differ between substances?
- Has predictability changed over time?
- Can we identify predictors of mortality?
- What are the key differences between short-term rehab and non-intensive outpatient?
- Do secondary substances impact predictability?

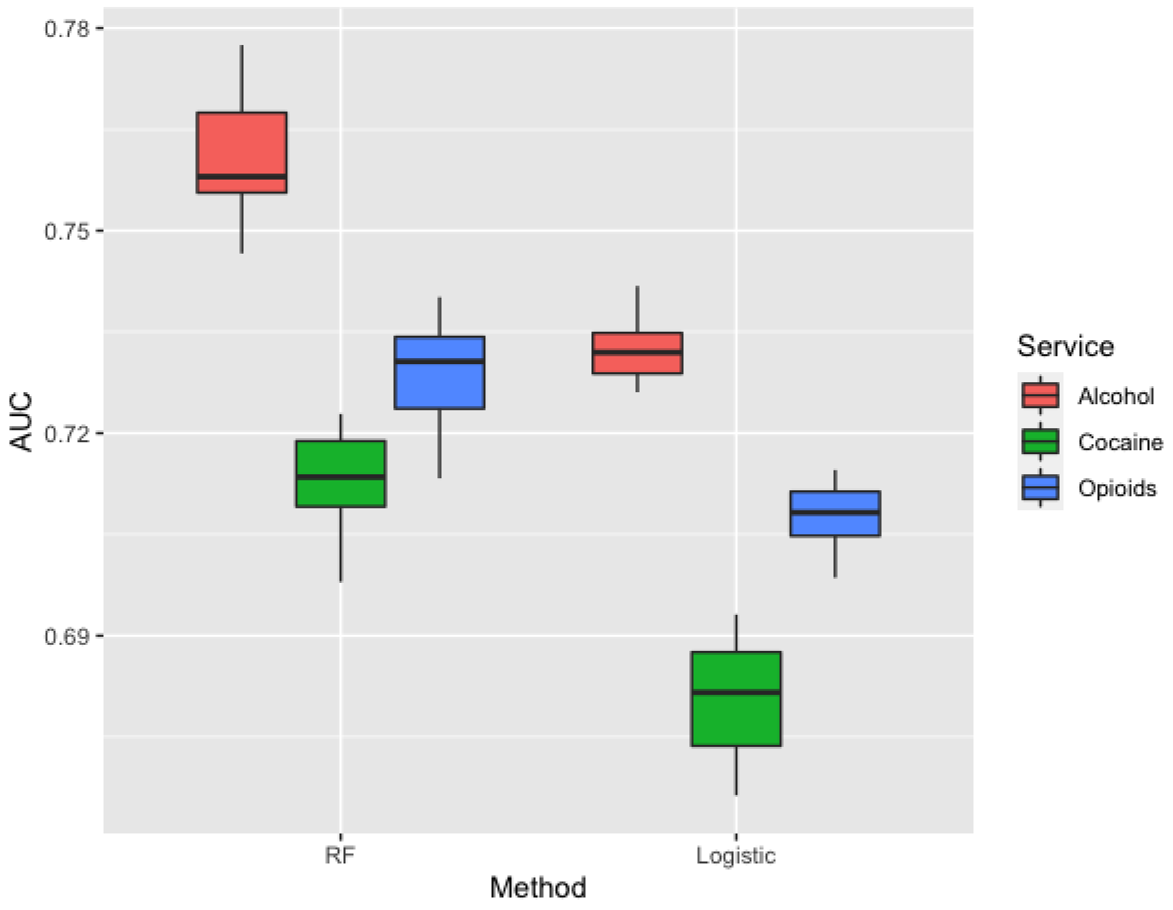
Year: 2018
Substance: Opioids, Cocaine, Alcohol
Treatment: Residential rehab

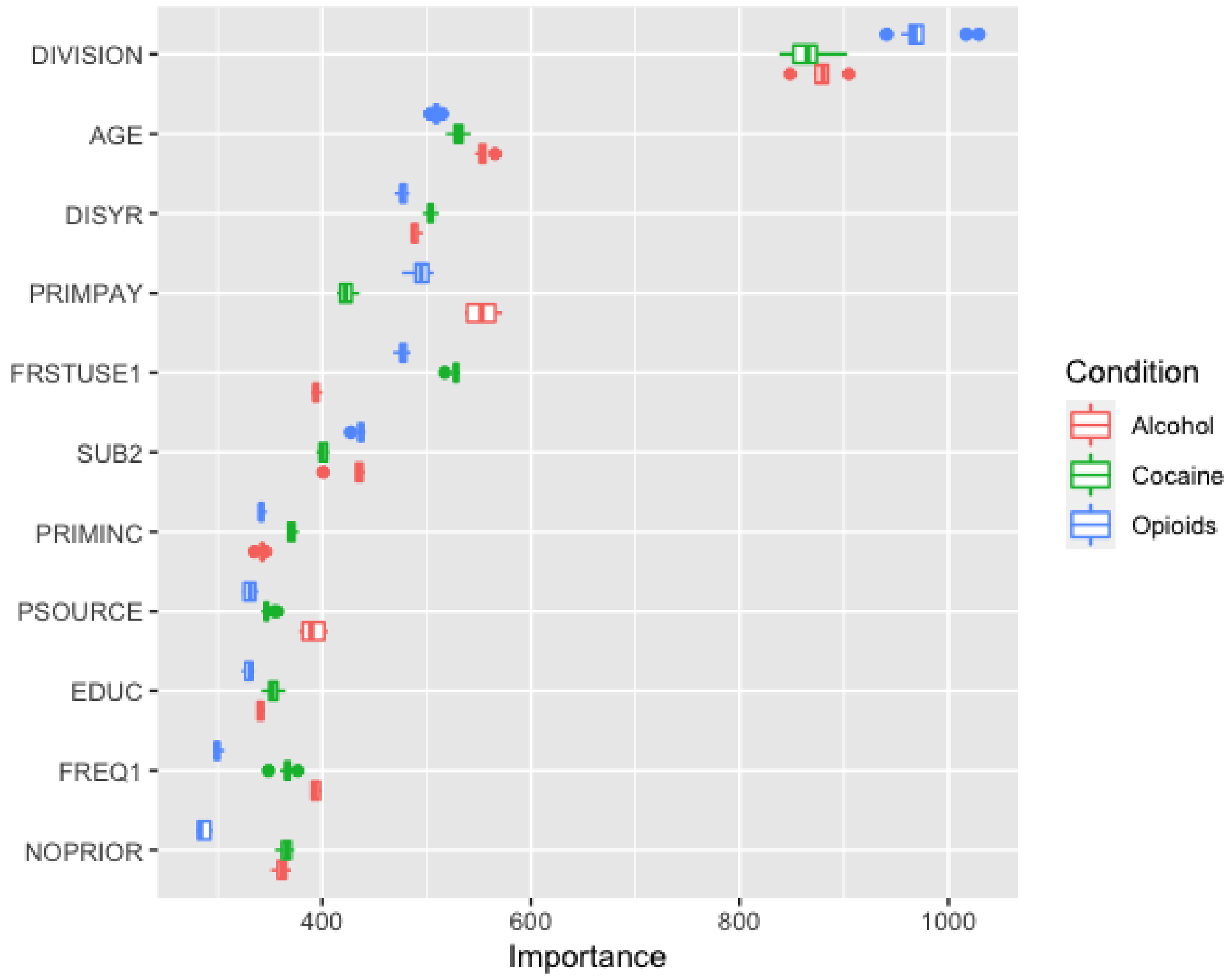
Total people in treatment per substance, by race and education level

Substance	Black, non-Hispanic	Hispanic or Latino	White, non-Hispanic	College	High school	No high school	Some college	Some high school
Alcohol	92275	1735	298258	50877	219789	25887	108695	74028
Cocaine	37154	336	39151	4433	43073	5426	17448	20624
Opioids	58004	1813	368718	23522	252166	27616	104645	93706

Predictability across substances

Year: 2010-2018
Substance: Opioids, Cocaine, Alcohol
Treatment: Residential rehab
Response: Treatment completion





Middle Atlantic

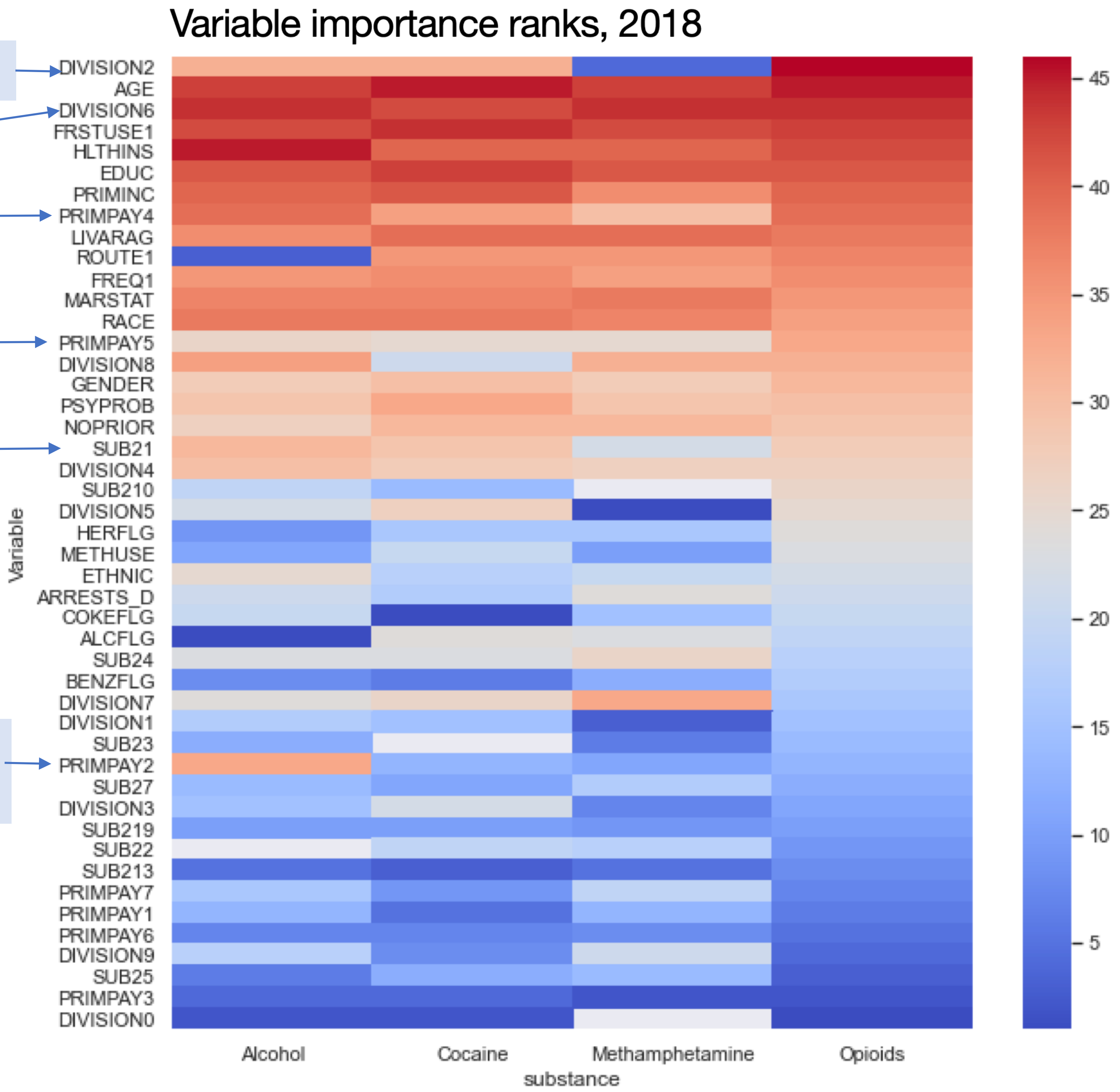
East South Central

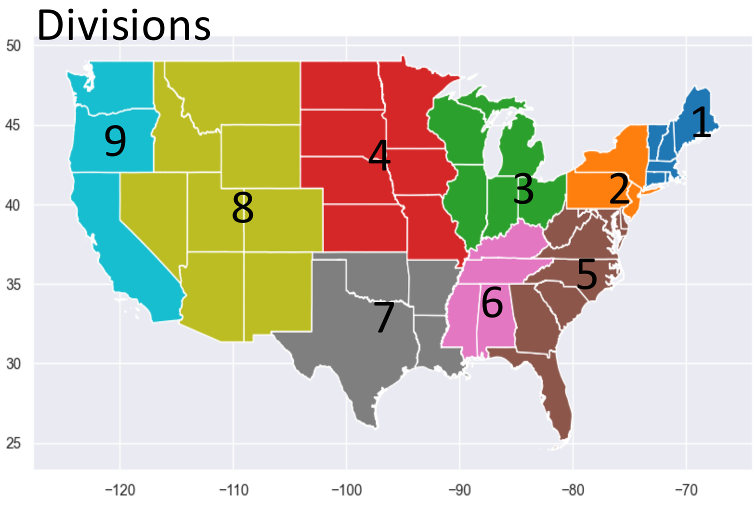
Medicaid

Other govt. payments

No secondary substance

Private Insurance

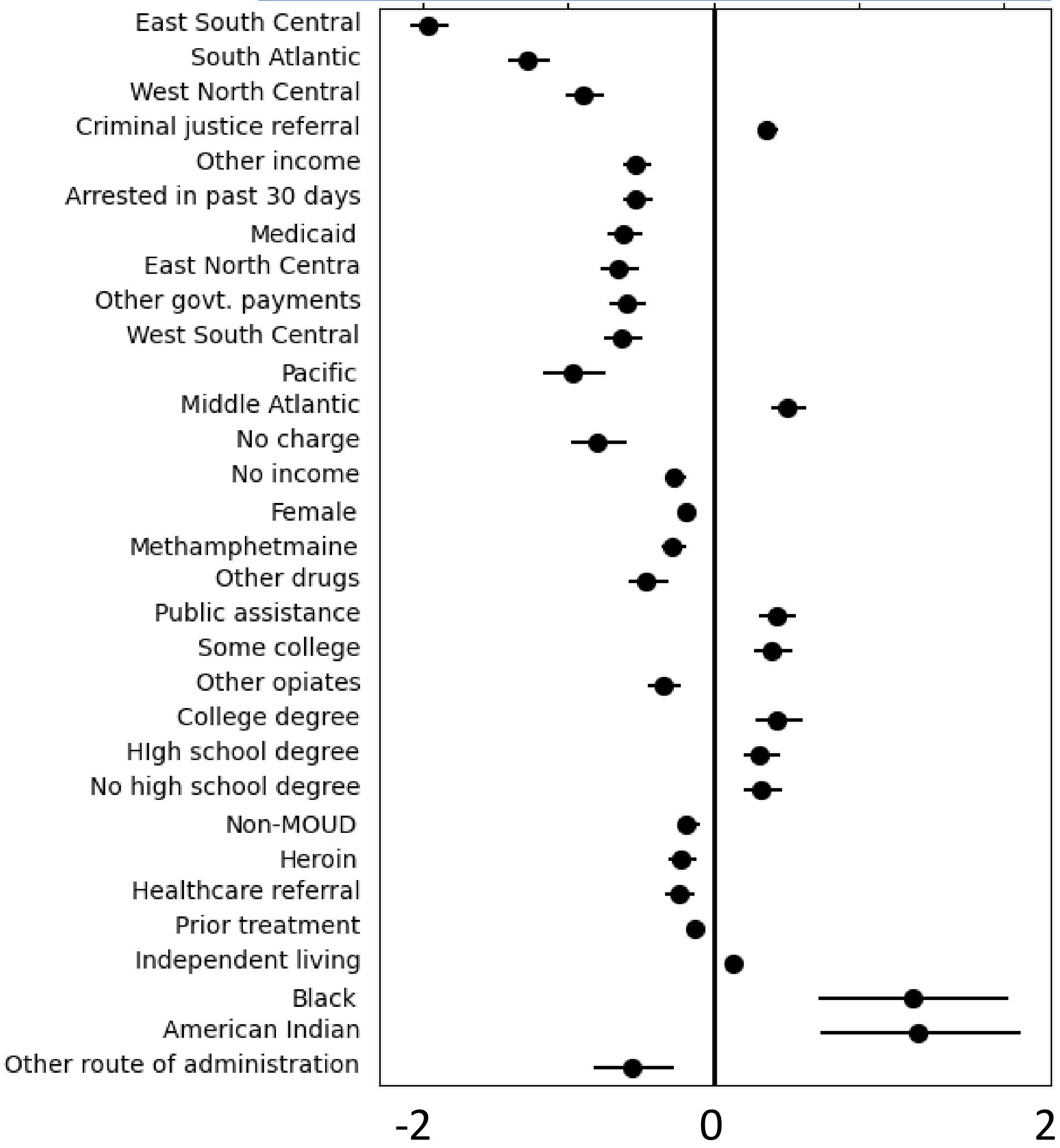




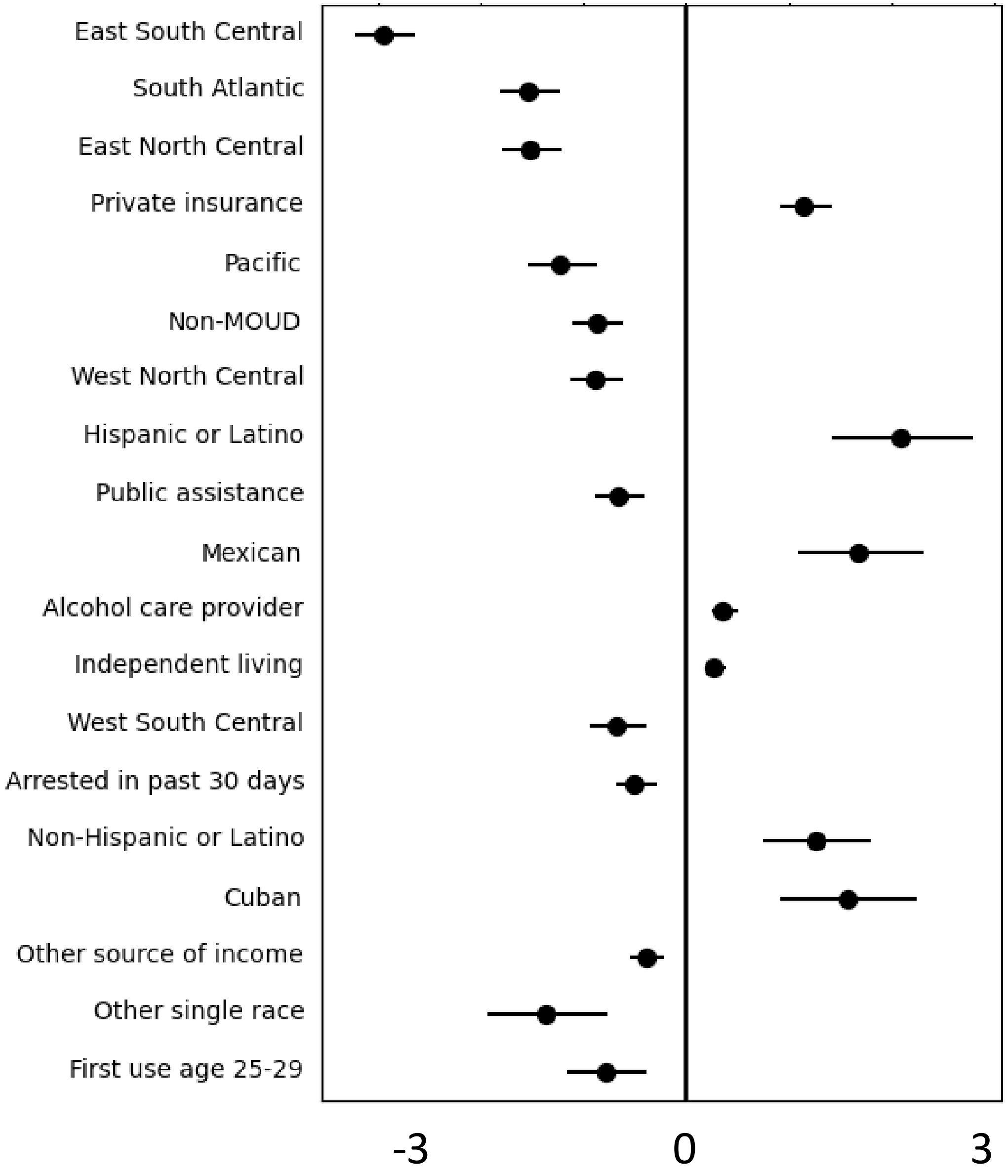
Treatment: Residential rehab

Response: Treatment completion

Logistic regression coefficients for **Opioids, 2018**

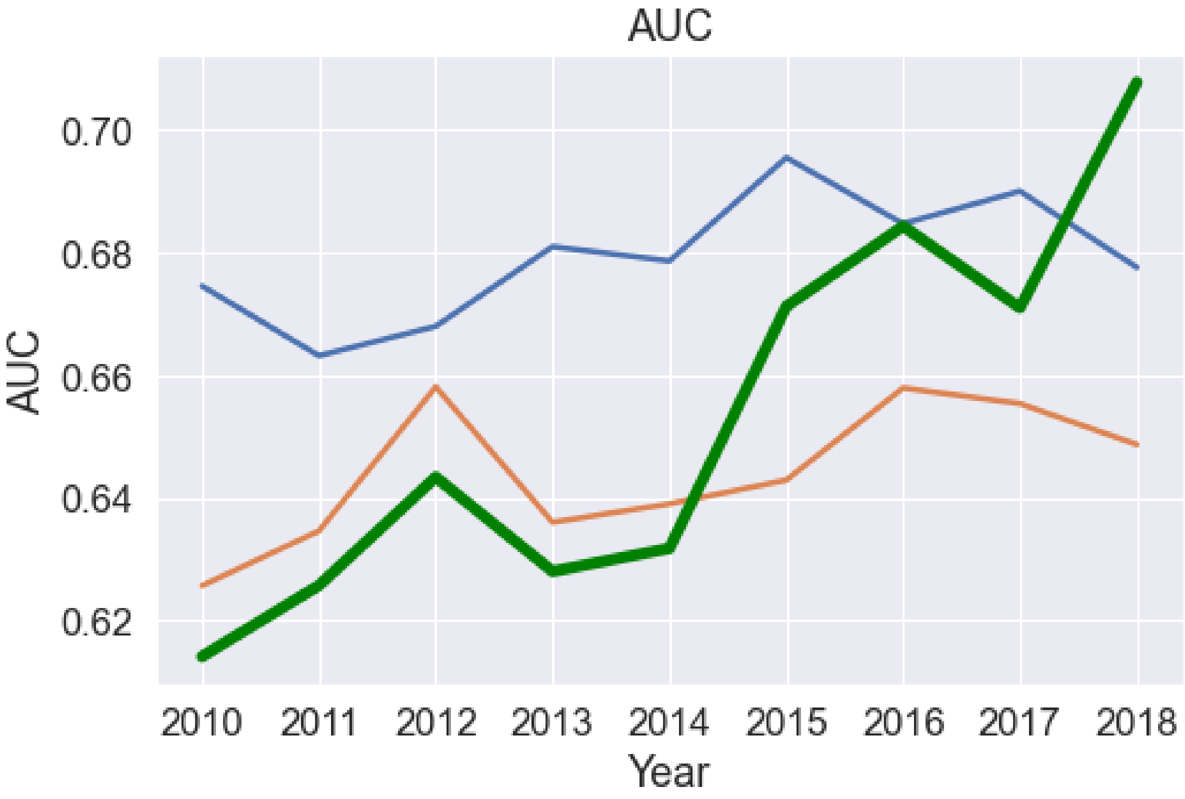


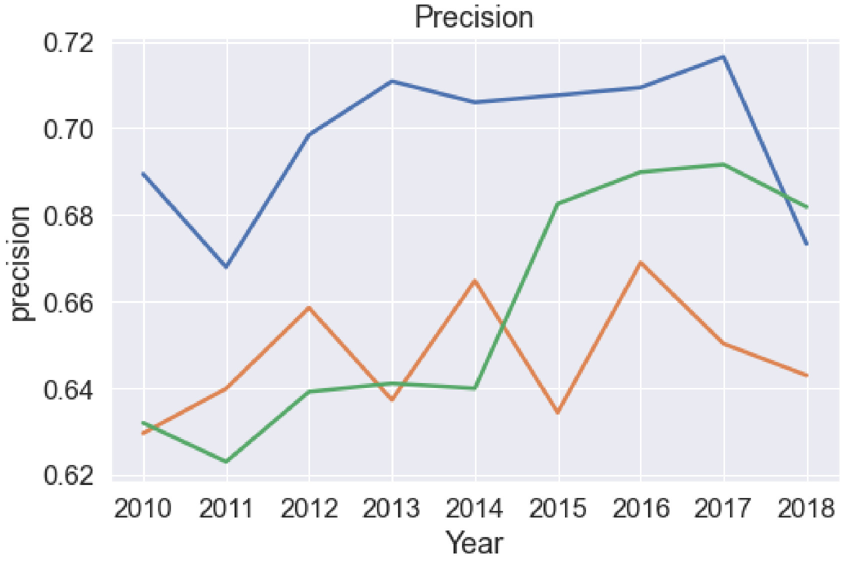
Logistic regression coefficients for **Alcohol, 2018**

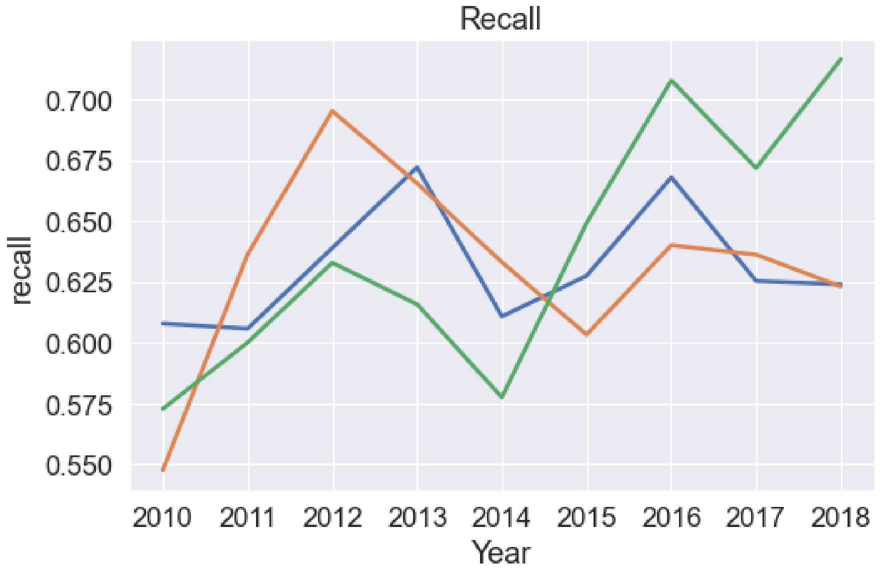


Year: 2018
Treatment: Residential rehab
Response: Treatment completion

Temporal trends





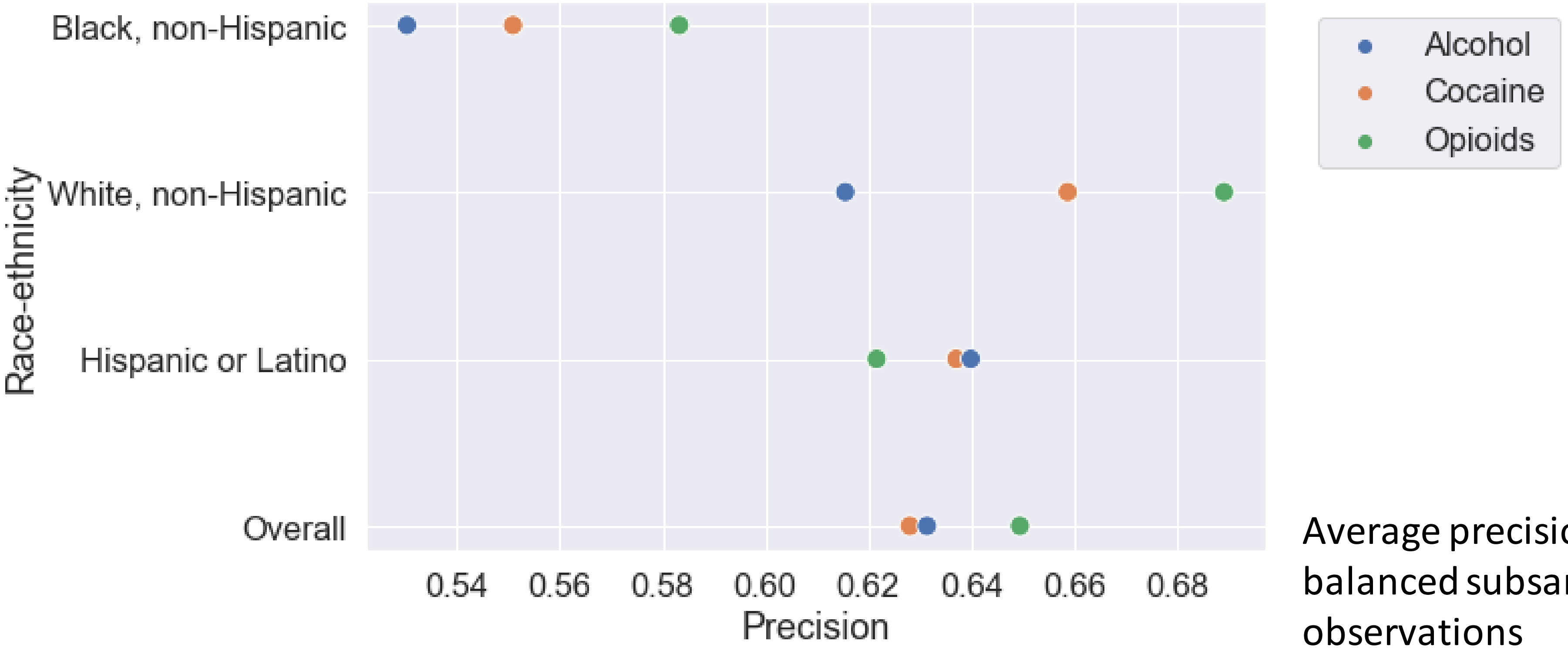


Year: 2010-2018
Substance: Opioids, Cocaine, Alcohol
Treatment: Residential rehab
Response: Treatment completion

Averaged across
10 balanced subsamples of
10k observations

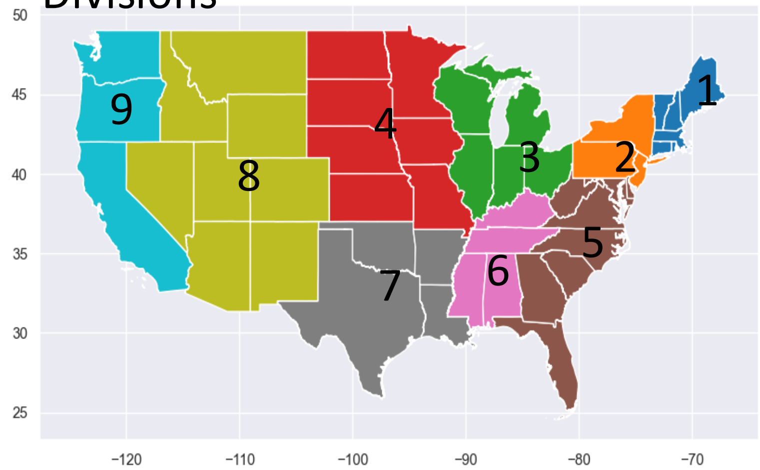
Are the predictions fair?

Year: 2010-2018
Substance: Opioids, Cocaine, Alcohol
Treatment: Residential rehab
Response: Treatment completion



Average precision across 10 balanced subsamples of 10k observations

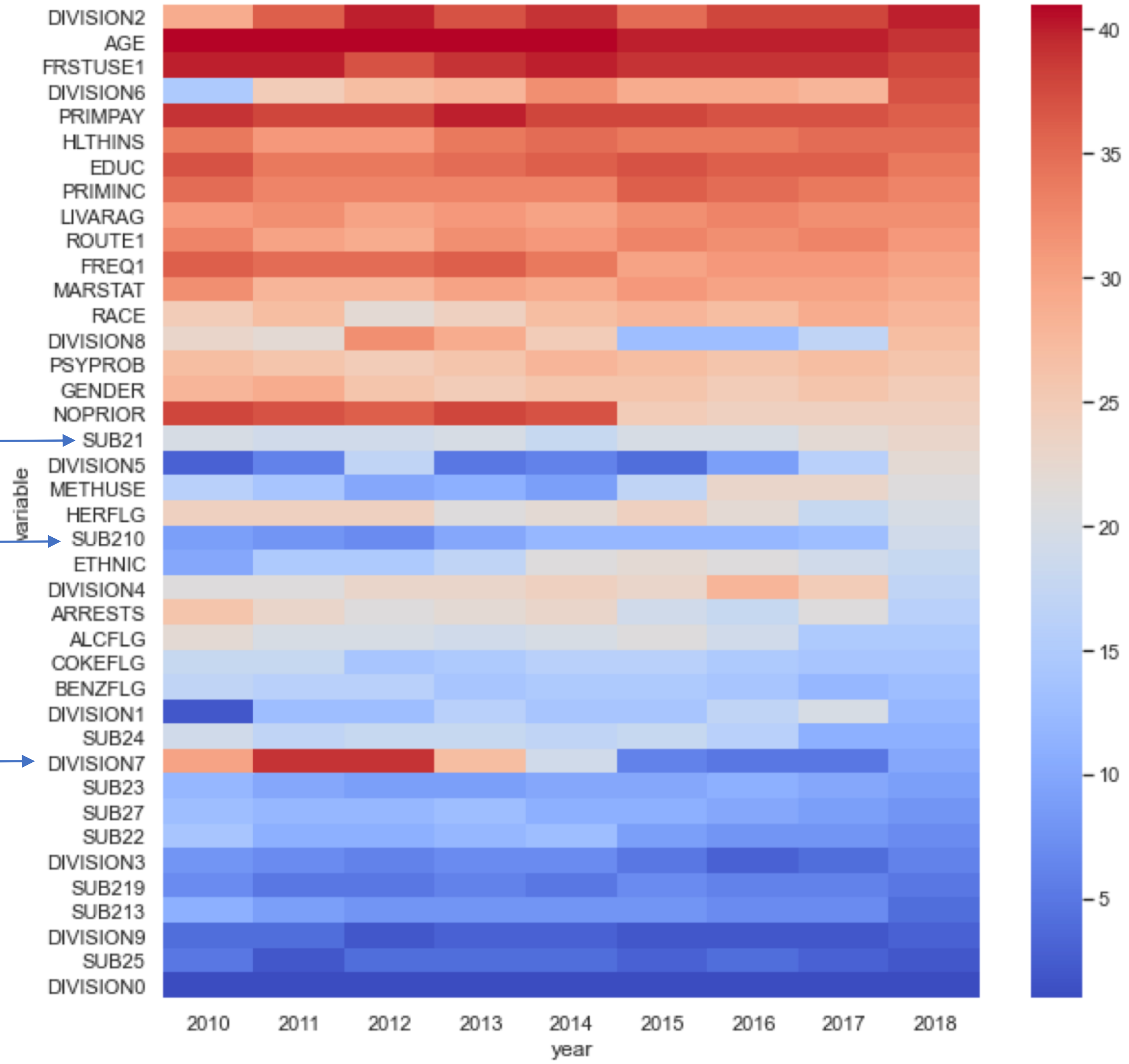
Divisions



No secondary substance

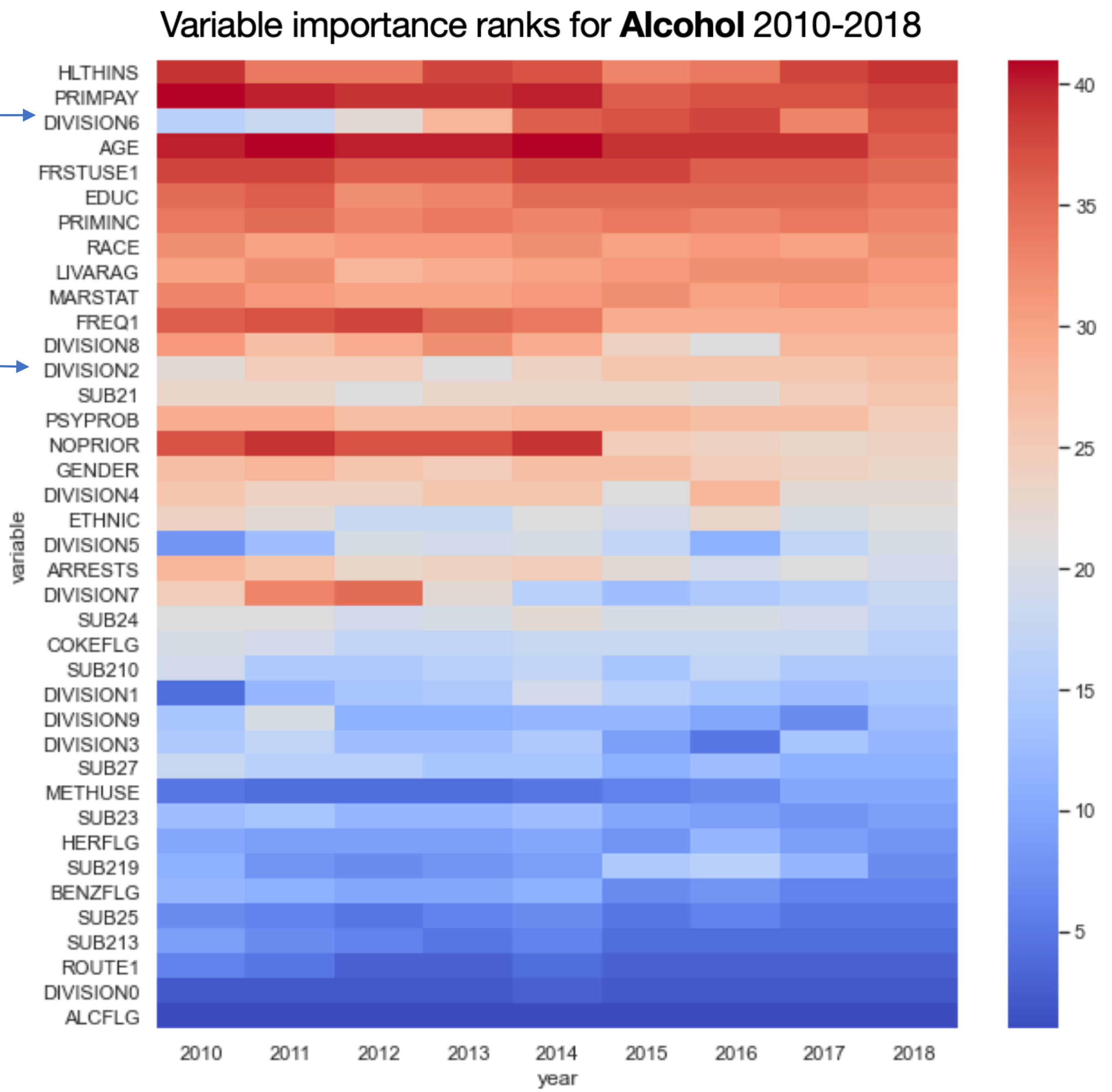
Meth as secondary substance

West South Central



Treatment: Residential rehab

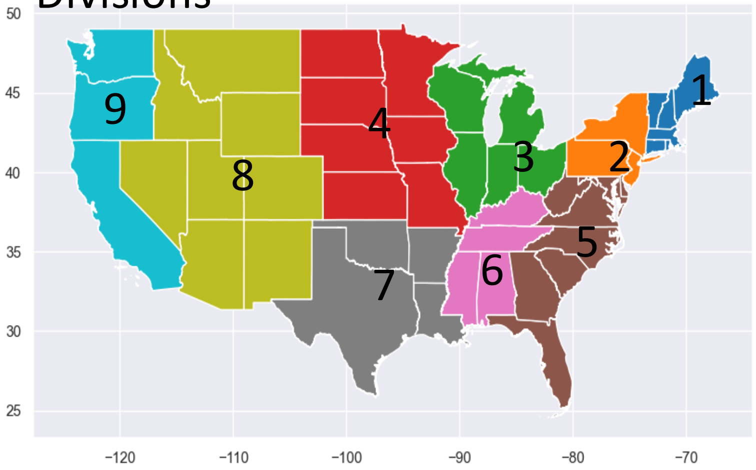
Response: Treatment completion



East South Central

Middle Atlantic

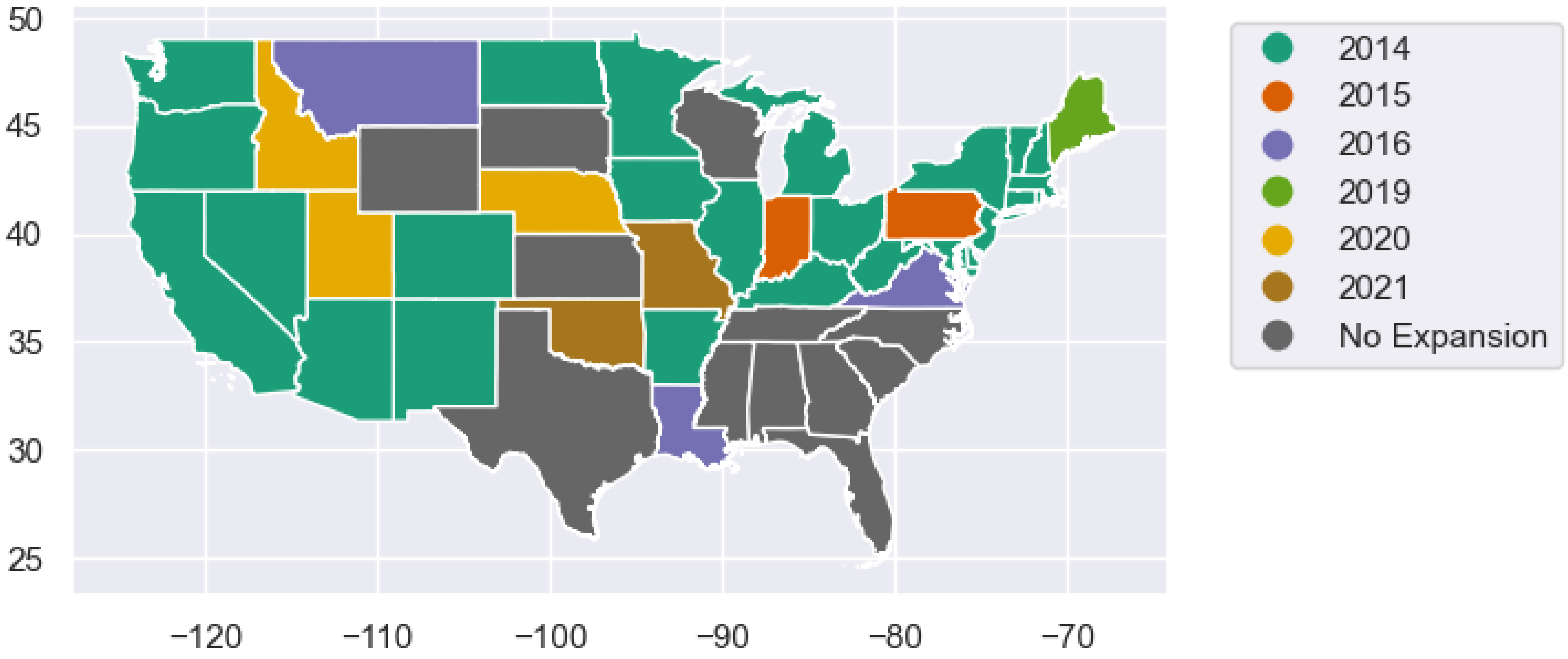
Divisions



Treatment: Residential rehab

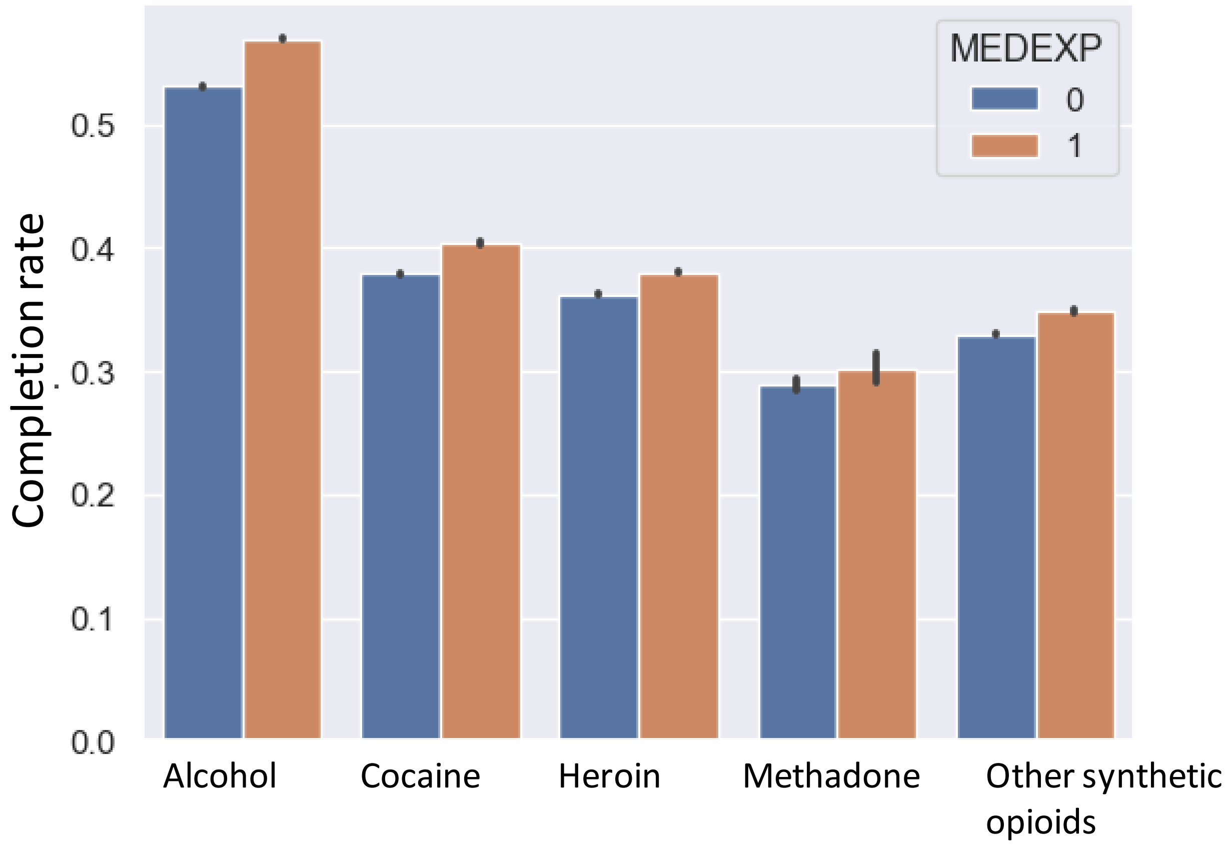
Response: Treatment completion

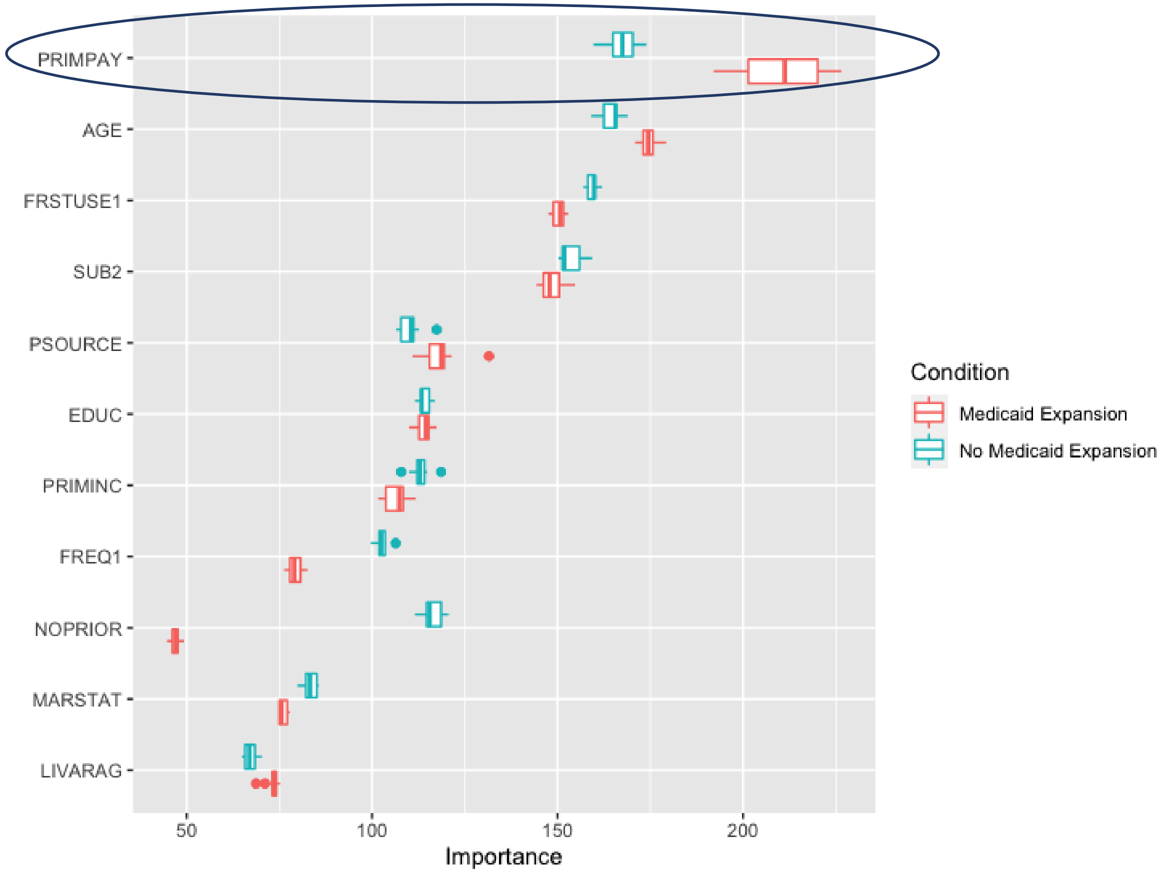
Medicaid expansion



Medicaid expansion

Year: 2010-2018
Substance: Opioids
Treatment: Residential rehab in Medicaid expanded vs. non-expanded states
Response: Treatment completion
"DIVISION" was removed as a predictor





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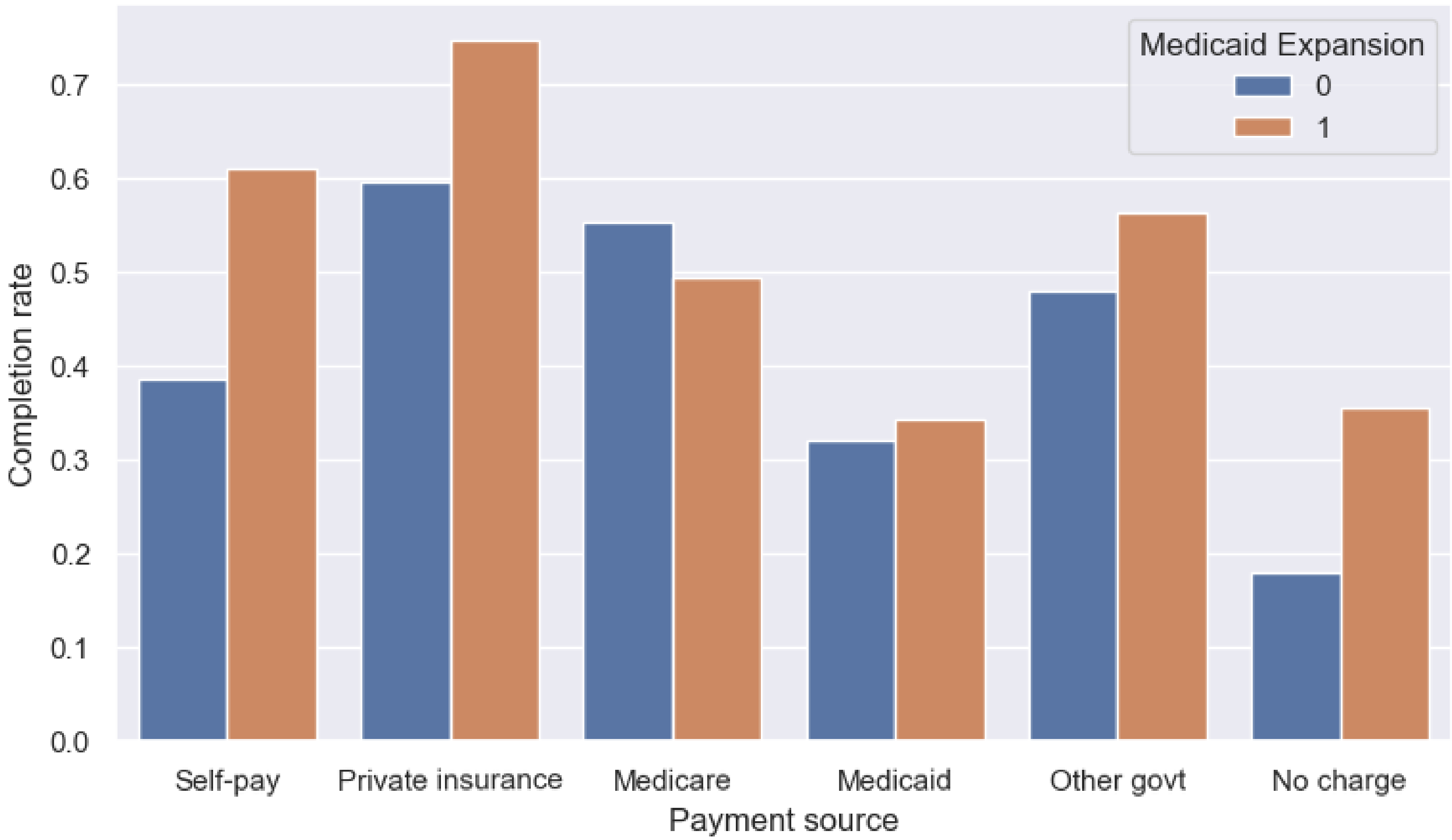
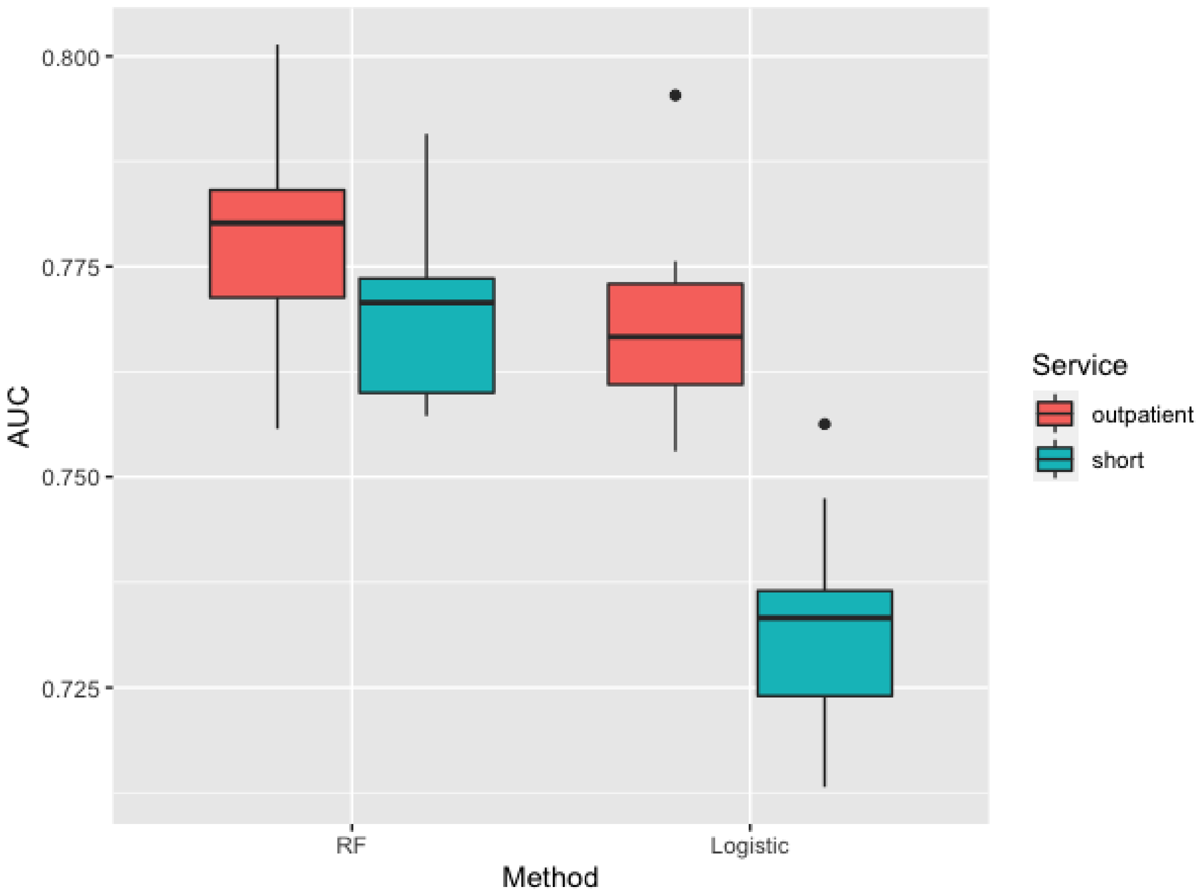
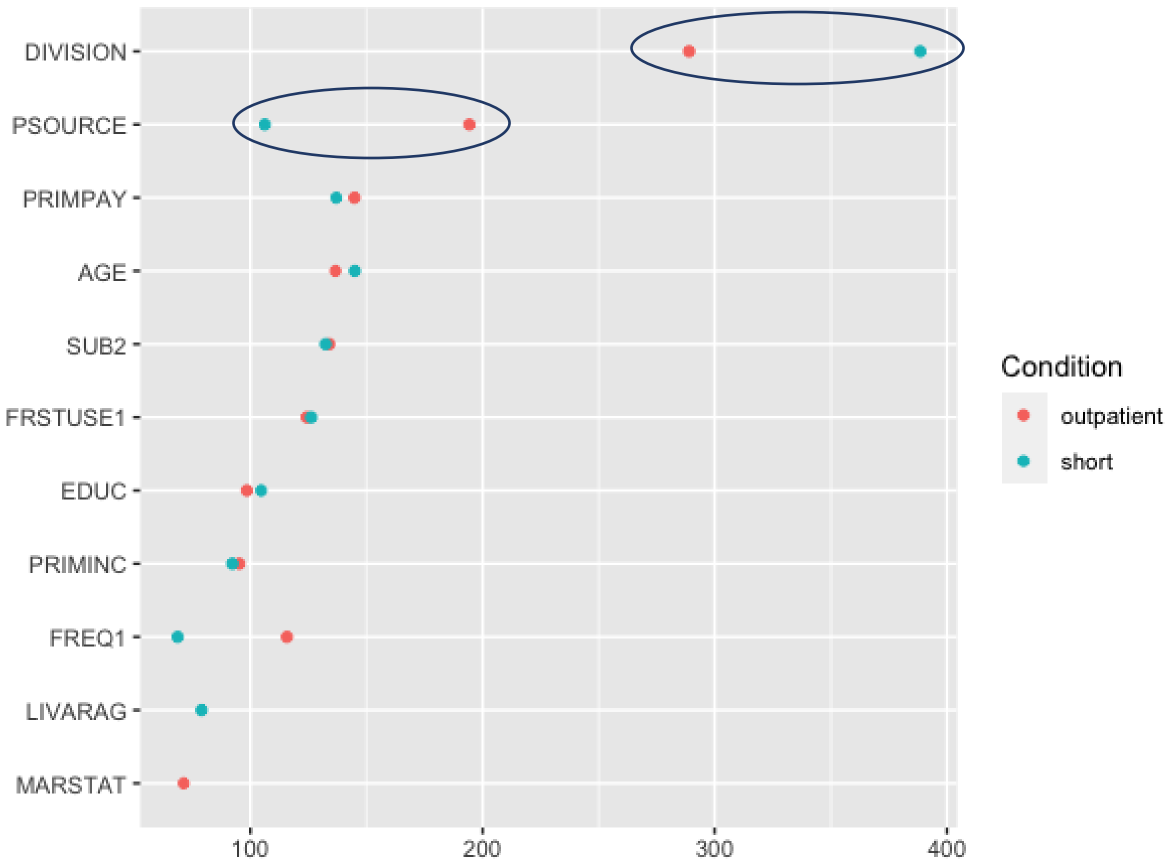


Year: 2018
Substance: Opioids
Response: Treatment completion

Short-term rehab vs. non-intensive outpatient treatment

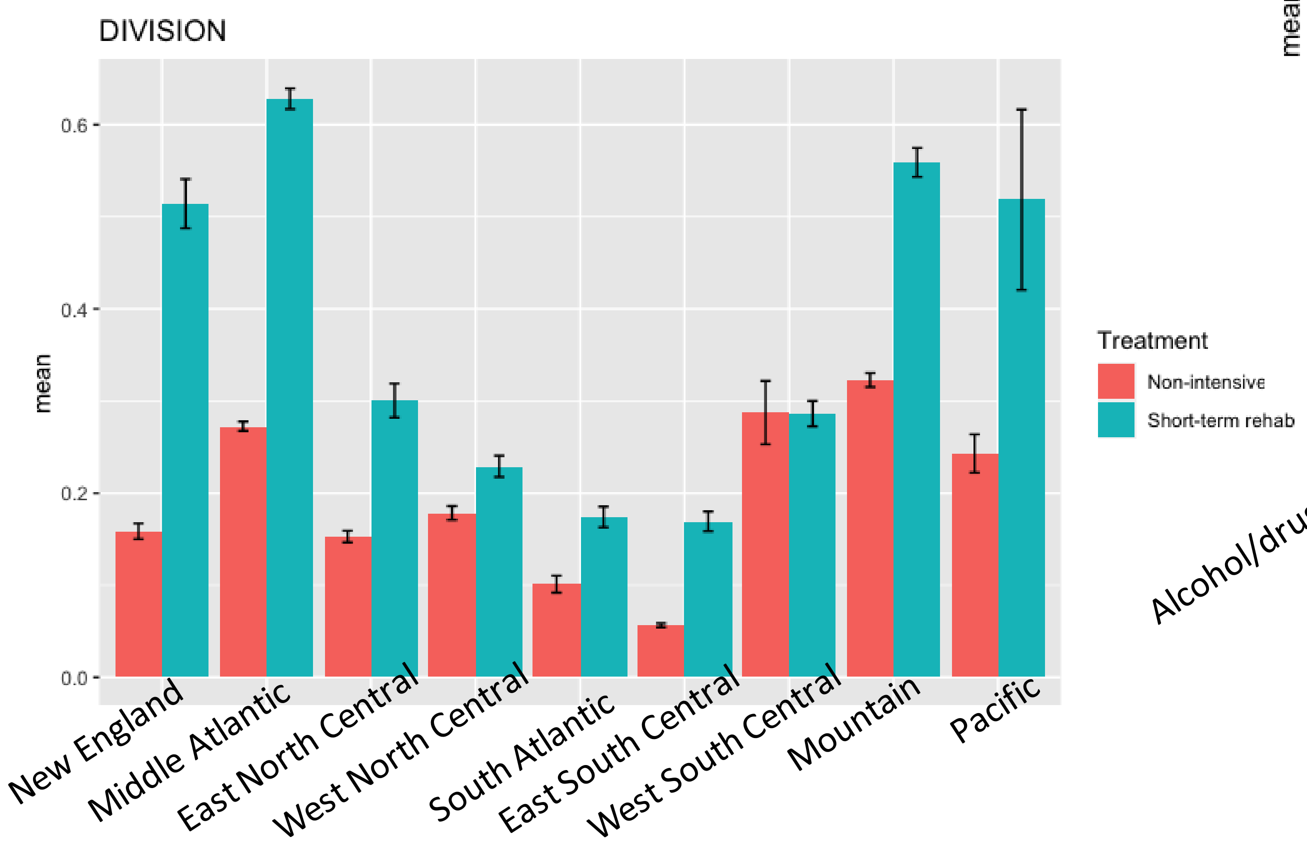


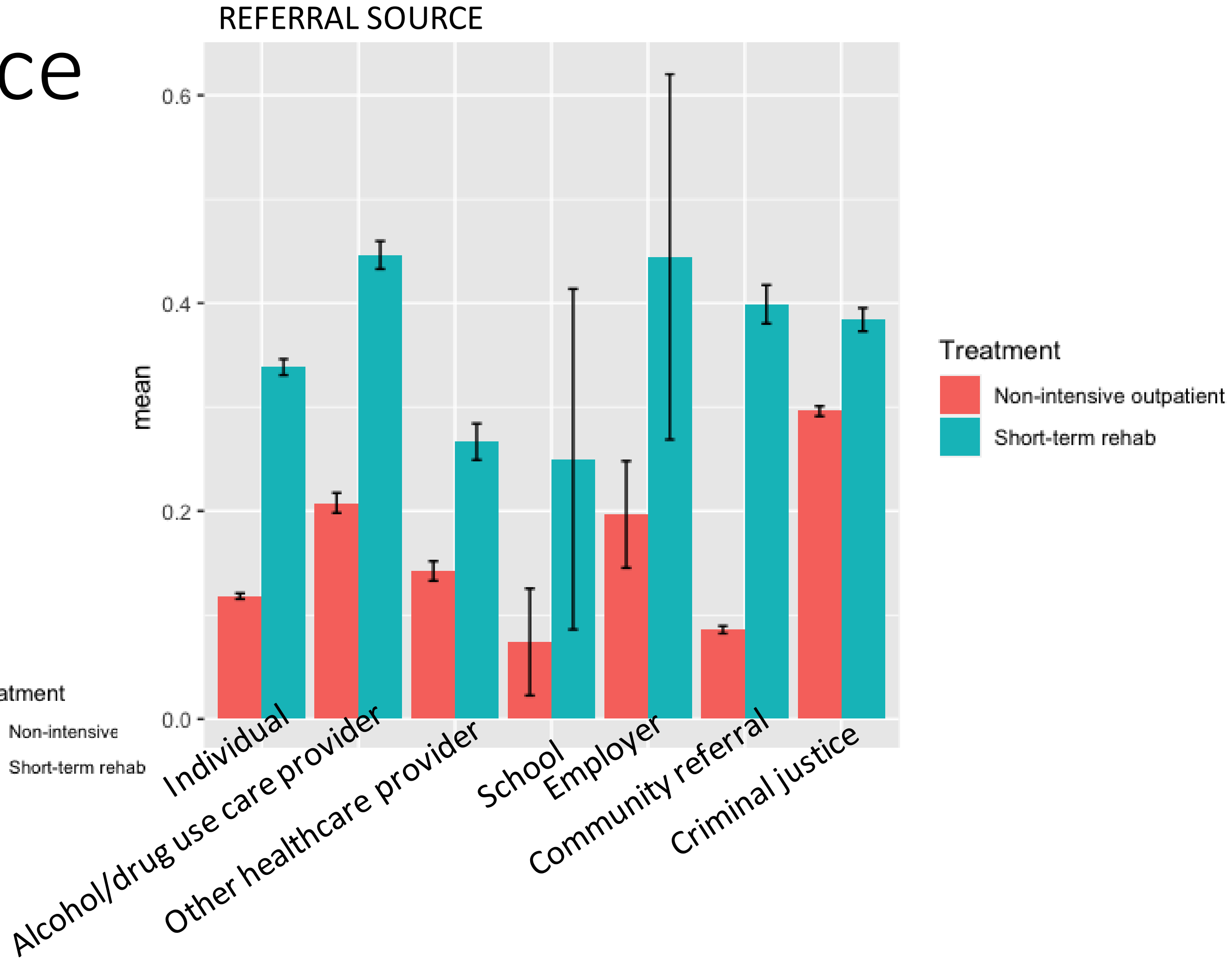
Variable importance from Random Forest



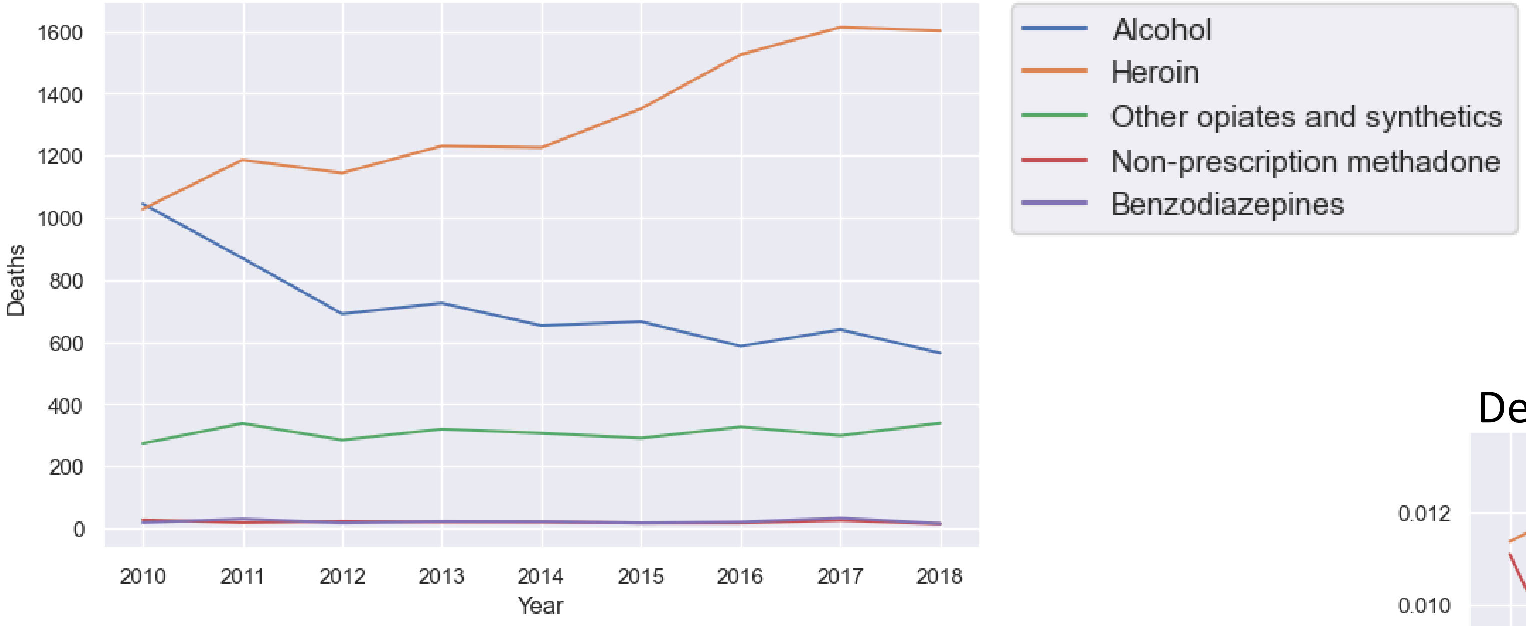
Variable Importance

Variables whose importance diverged between groups

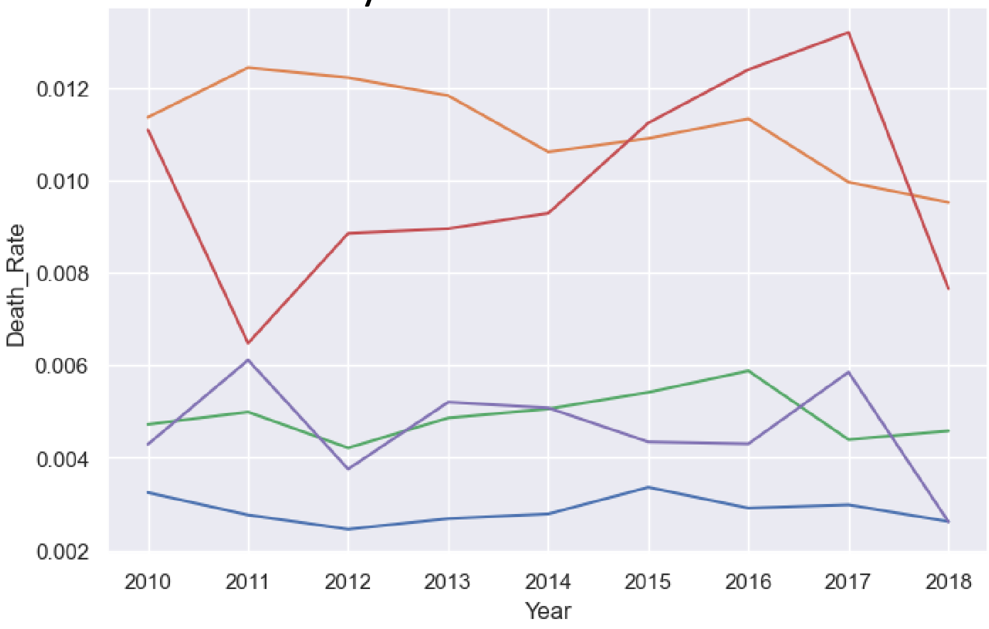




Total yearly deaths occurring during non-intensive outpatient treatment



Death rate by substance

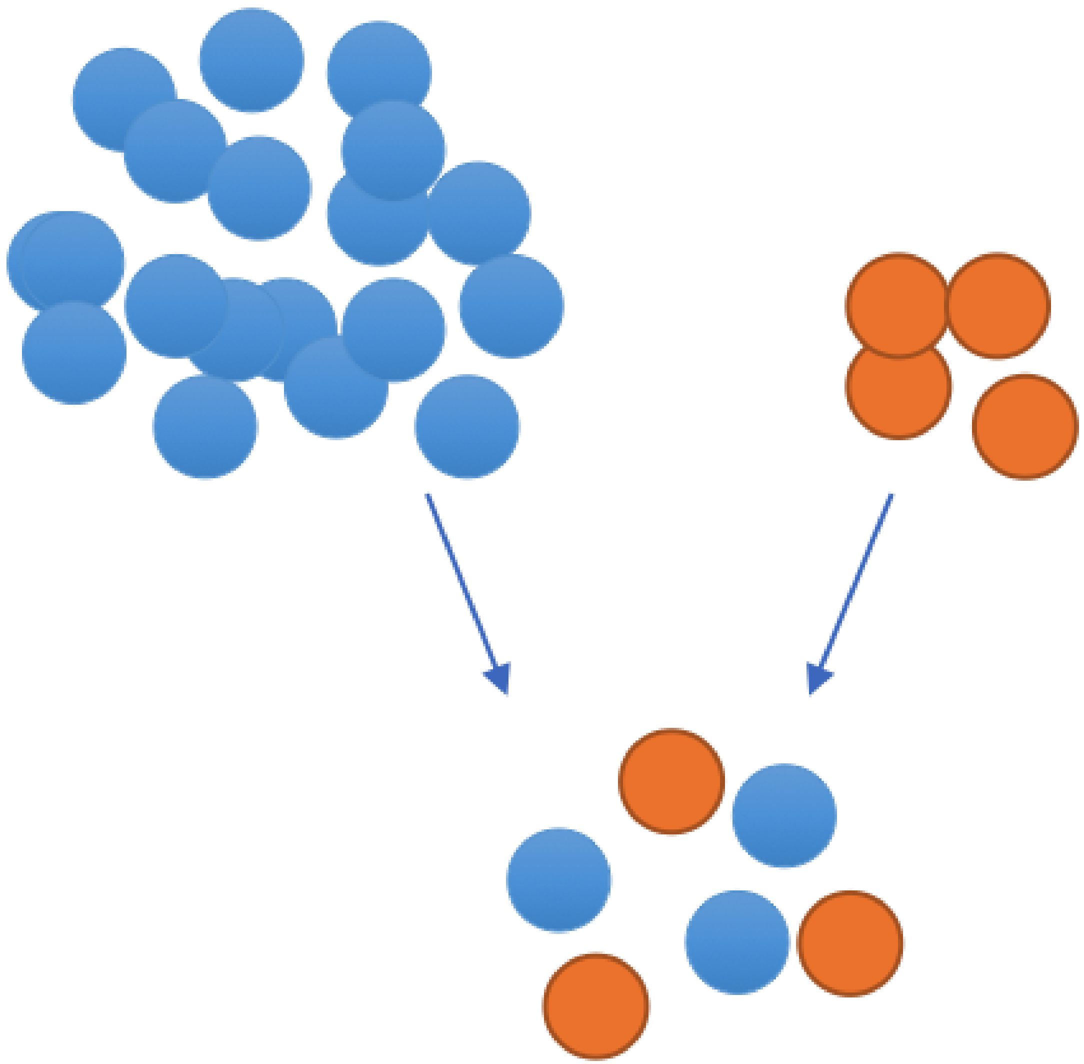


- Deaths while in treatment are rare, occurring in only 0.2% of cases
- Non-intensive outpatient deaths account for >80% of all <u>observed</u> deaths across treatments
- Death not so rare in outpatient opioid disorder treatment.

Downsampling for imbalanced classes

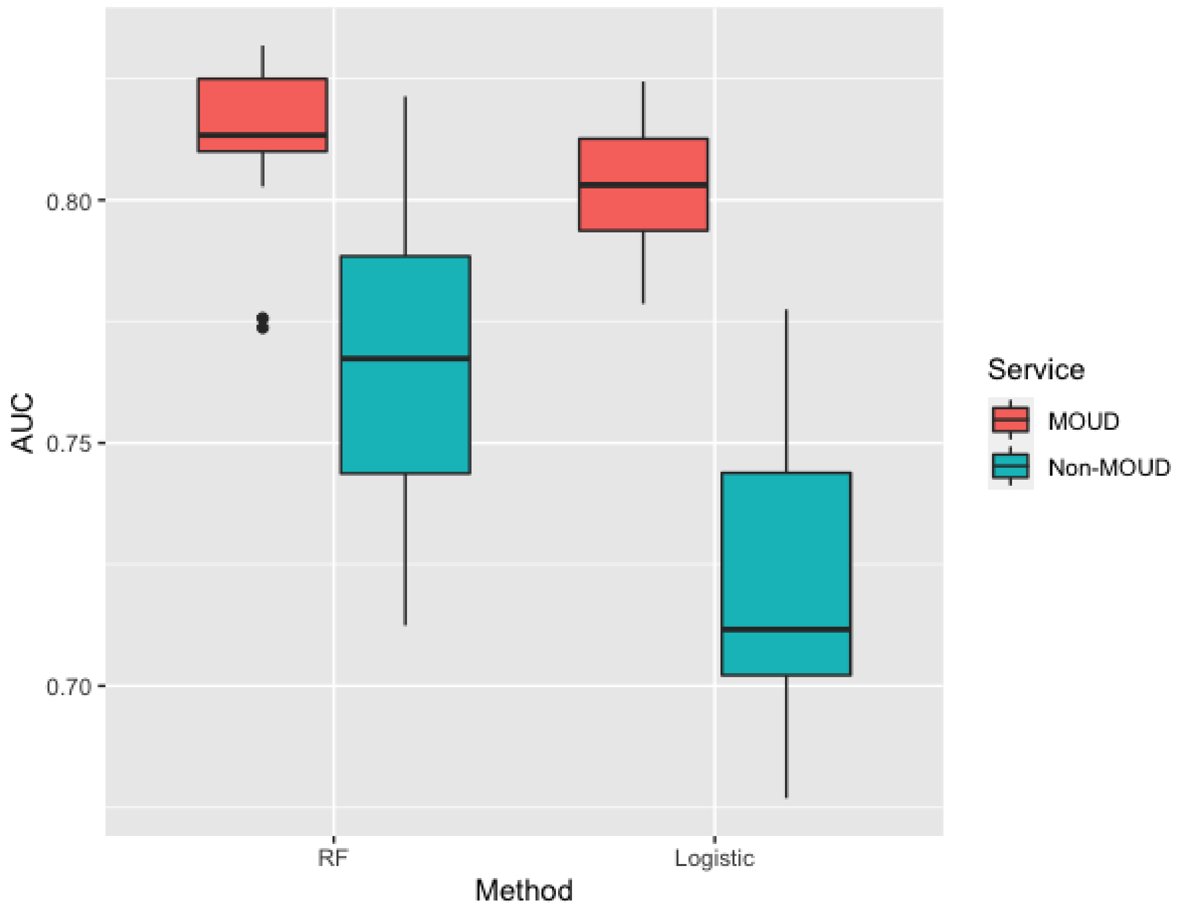
When one of the classes makes up just a small fraction of the training data, the model will spend most of its time learning from the other class

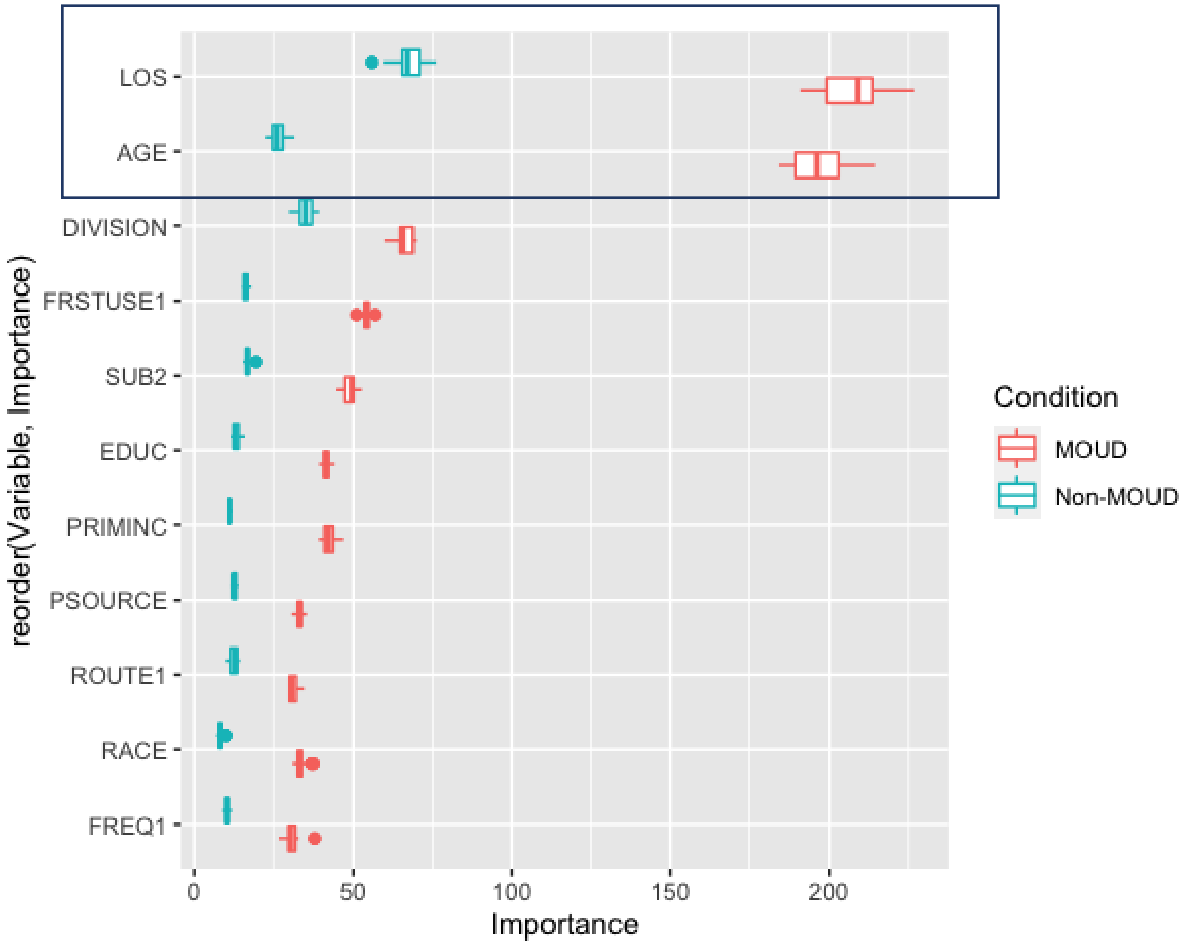
Solution: dowsampling



MOUD & Mortality

Year: 2018
Substance: Opioids
Treatment: Non-intensive outpatient
Response: Treatment terminated by death





MOUD & Mortality

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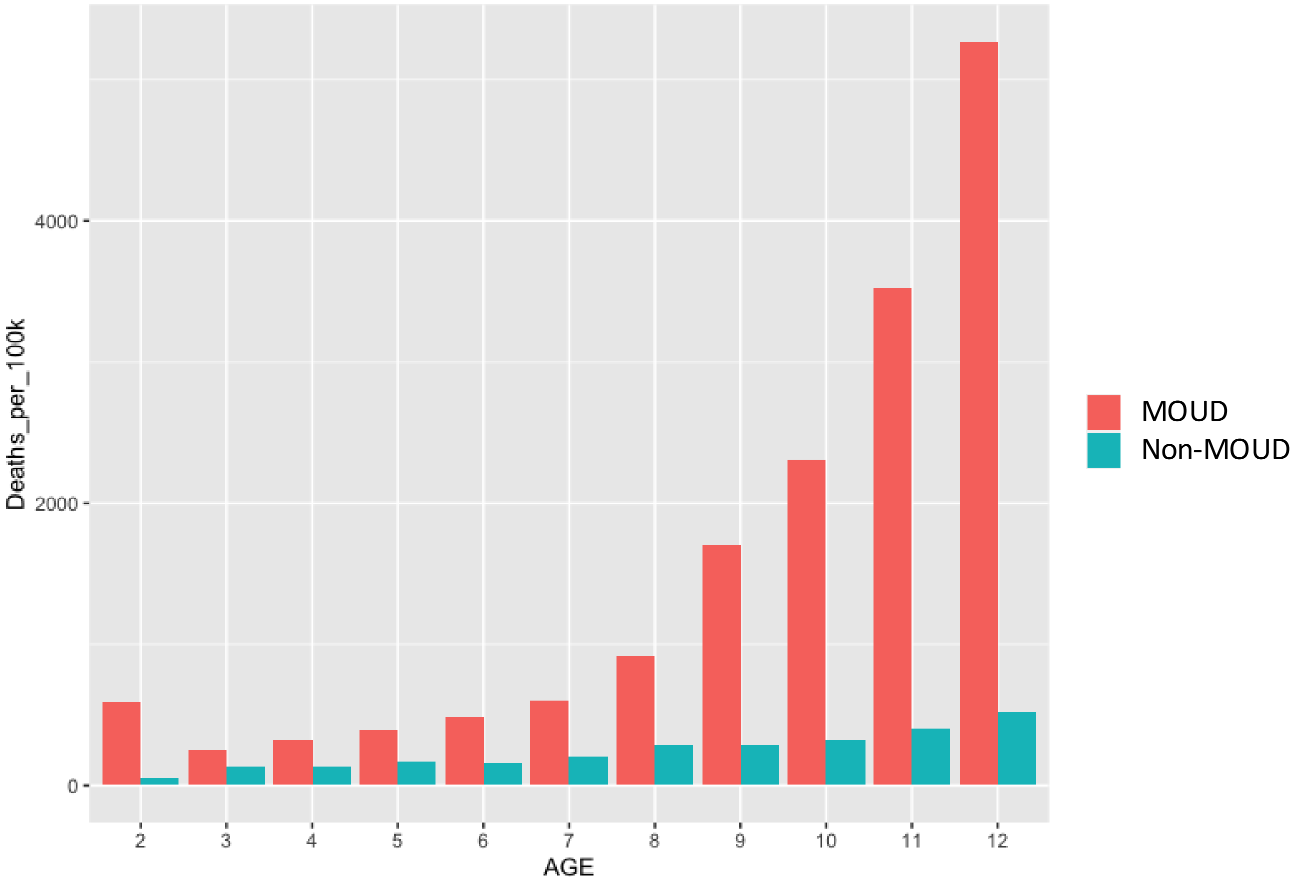

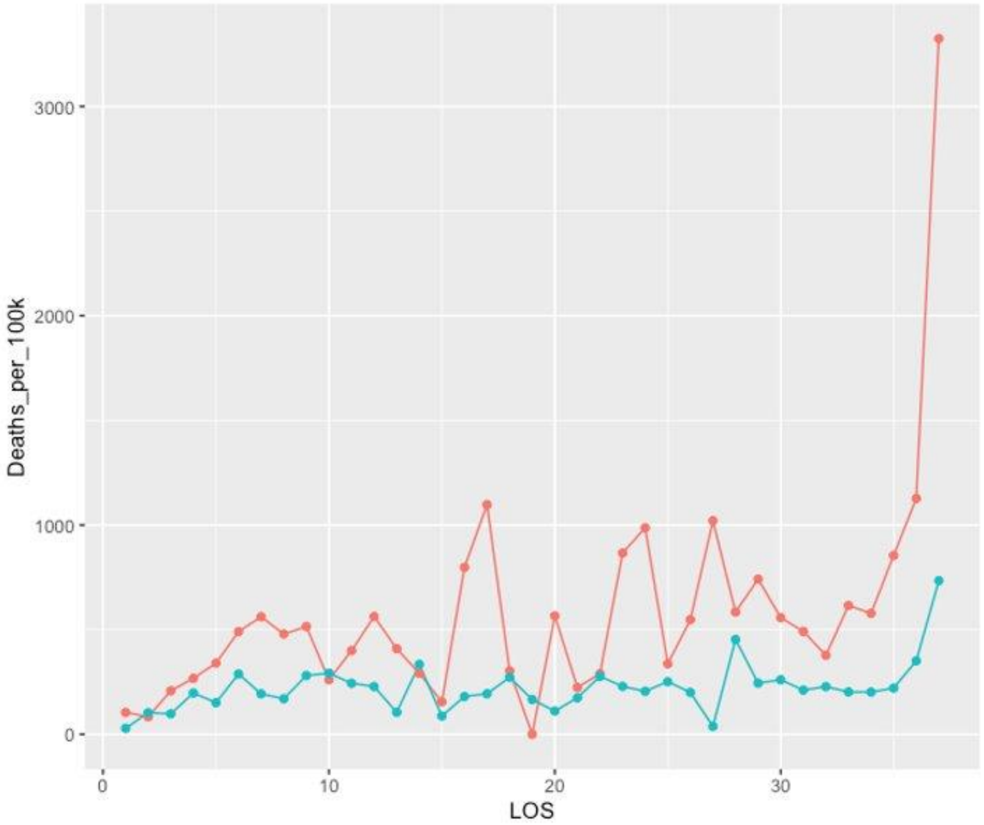

Motivates further investigation

Conclusions

- Machine learning offers modest but real predictive boost
- Important variables emerge from the model to help direct further analyses
  - Predictability of successful completion of opioid residential treatment has increased since 2010; not true for alcohol/cocaine.
  - Geography consistently emerges as a strong predictor
    - Note for further studies: this could potentially be linked to reporting bias. Should treat carefully.
  - MOUD + age/length of stay linked to opioid mortality—not a causal link, but an important marker and clinical reality in this space.