

An Open Benchmark for Causal Inference Using the MIMIC-III and Philips Datasets

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Goal

Create an open, public benchmark for causal inference from observational hospital data

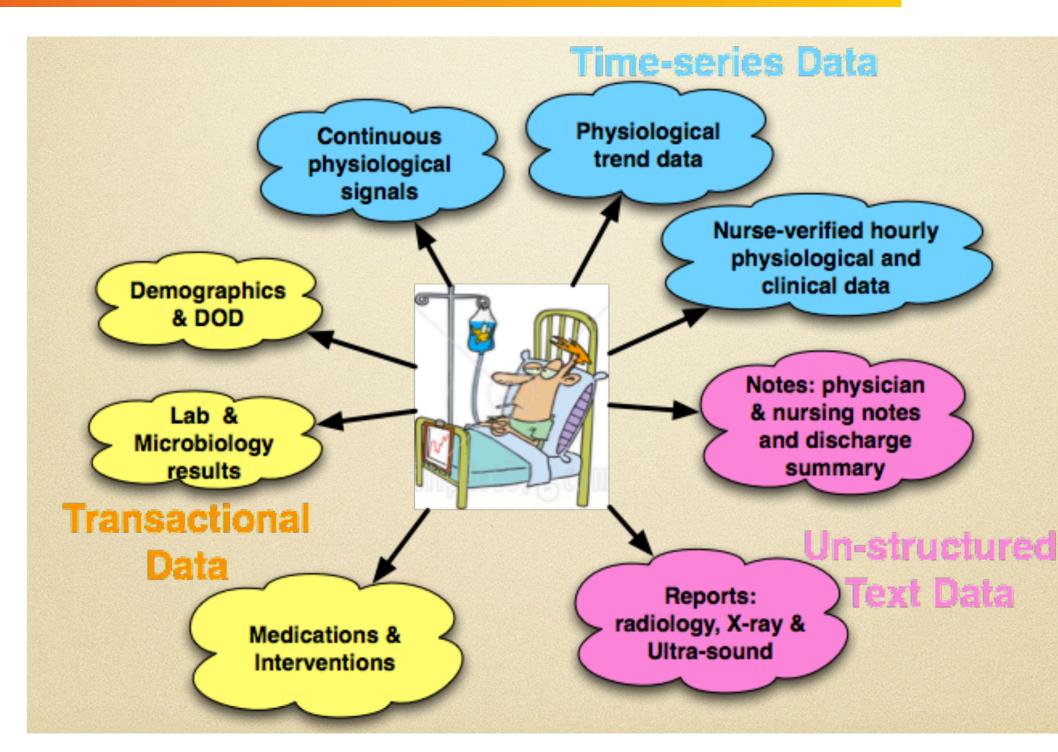
Background

- Large scale observational datasets: promise of inferring new causal relationships
- Massive and diverse datasets

 require new statistical methods
- Challenge: how to compare and evaluate observational causal inference methods?
- Solution: identify RCTs conducted within observational datasets

Open hospital ICU datasets

- Two public de-identified datasets:
 MIMIC-III and Philips (released early 2017)
- More than 250,000 ICU admissions of ~200,000 adults over 11 years at dozens of hospitals across the USA
- Demographics, vital sign measurements made at the bedside (~1 data point per hour), laboratory test results, procedures, medications, caregiver notes, imaging reports, mortality (both in and out of hospital)



Patients linked between files using unique member ID

Image: Mengling Feng

Benchmarking Causal Inference for Observational Studies

	Real-world confounders	Real-world treatment assignment	Real-world outcomes	Compare study designs	Public
2016 Atlantic Causal Inference Competition		X	X	X	
Adverse drug reaction, Ryan et al. (2012)					X
Proposed benchmark				X	

Methods

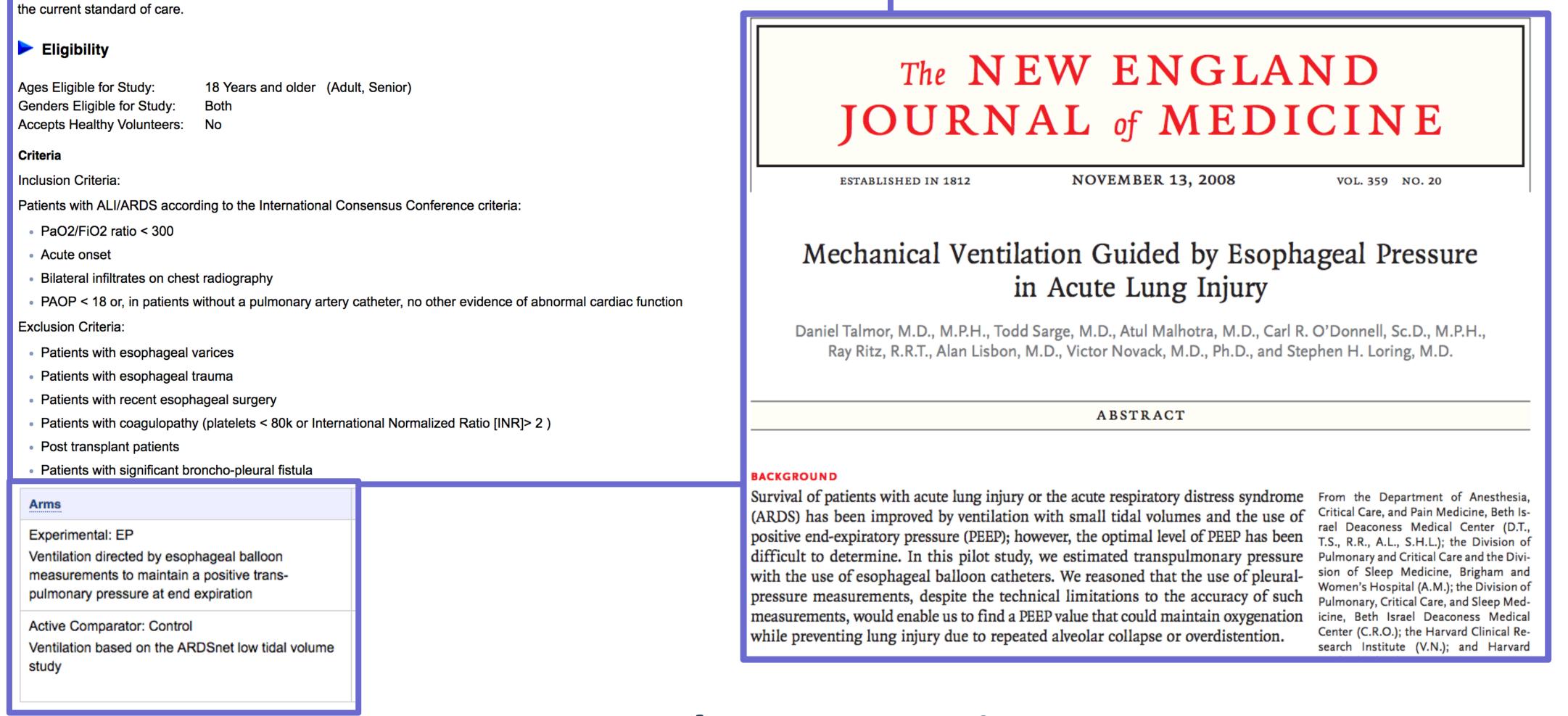
- Identify RCTs performed in ICUs similar to the MIMIC/Phillips ICUs
- Identify cohorts equivalent to the RCT cohorts within the public datasets using OMOP CDM
- Only small subset of eligible RCTs can plausibly be replicated
 - Treatment, outcome, inclusion/exclusion criteria, important background variables (confounders)

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- For each identified RCT: treatment (T=0,T=1) and outcome Y Average Treatment Effect ATE = $\mathbb{E}[Y|T=1] \mathbb{E}[Y|T=0]$
- Identify potential confounders in observational cohort
- Create and publish easily accessible datasets for researchers outside of the medical informatics community, in two forms:
 - (Confounder, Treatment, Outcome)
 - Cohort creation script
- Baseline observational study
 - Based on OHDSI CohortMethod, propensity score and matching
 - Non-linear methods such as Bayesian Additive Regression Trees
- In 2017 run a public competition for inferring the RCT ATE from the published observational datasets

Candidate studies (preliminary)

clinicaltrials.gov



MIMIC-III cohort: 92 patients