“Who[1] experiences large model decay and why[2]?”

A Hierarchical Framework for Diagnosing Heterogeneous Performance Drift

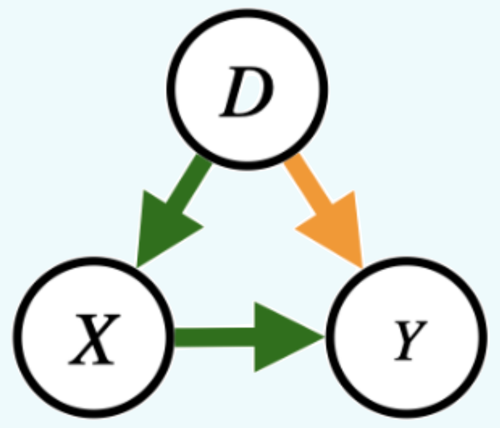
University of California San Francisco

Harvineet Singh[1], Fan Xia[1], Alexej Gossmann[2], Andrew Chuang[1], Julian Hong[1], Jean Feng[1]

[1] University of California, San Francisco, [2] Independent

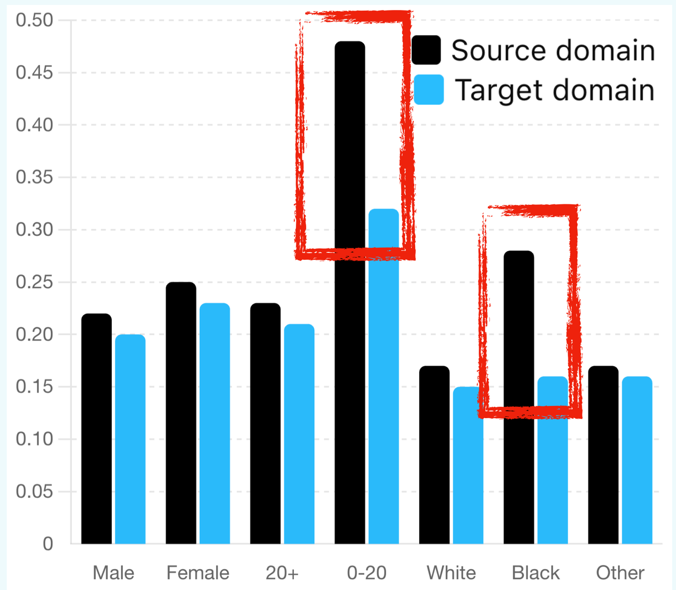
Motivation

- To understand differences in performance between a source domain ($D = 0$) and target domain ($D = 1$), existing methods decompose the *average* performance difference into contributions from **covariate** vs **outcome** shifts:



$$
\begin{aligned}
&\mathbb{E}_1[\ell(Y, f(X))] - \mathbb{E}_0[\ell(Y, f(X))] \\
&= \mathbb{E}_1[Z_0(X)] - \mathbb{E}_0[Z_0(X)] \\
&+ \mathbb{E}_1[Z_1(X)] - \mathbb{E}_1[Z_0(X)]
\end{aligned}
$$

where $Z_D(X) = \mathbb{E}_D[\ell(Y, f(X)) \mid X]$.



- However, ***performance differences can vary significantly across subgroups.***

Key contributions

- To help model developers better diagnose and mitigate large performance gaps, this work develops SHIFT, a hierarchical hypothesis testing framework that answers:
  1. ***(Who)*** Have covariate or outcome shifts led to unacceptably worse performance in any meaningfully large subgroup?
  2. ***(Why)*** If so, can these performance drops be explained by a sparse subset of variables in X?
- Unlike existing methods, SHIFT
  - Is nonparametric
  - Provides valid uncertainty quantification, even in settings with potentially limited data
  - Does not require detailed causal knowledge

SHIFT: Subgroup-scanning Hierarchical Inference Framework for performance drifT

Aggregate Covariate Shift Hypothesis

H_0: For all subgroups A with size $\geq \epsilon$, the performance drift in A due to the aggregate covariate shift is no larger than pre-specified tolerance $\tau \geq 0$, i.e.

$$\mathbb{E}_1[Z_0(X) \mid X \in A] - \mathbb{E}_0[Z_0(X) \mid X \in A] \leq \tau.$$

Aggregate Outcome Shift Hypothesis

H_0: For all subgroups A with size $\geq \epsilon$, the performance drift in A due to the aggregate outcome shift is no larger than pre-specified tolerance $\tau \geq 0$, i.e.

$$\mathbb{E}_1[Z_1(X) \mid X \in A] - \mathbb{E}_1[Z_0(X) \mid X \in A] \leq \tau.$$

X_s-specific Covariate Shift Hypothesis

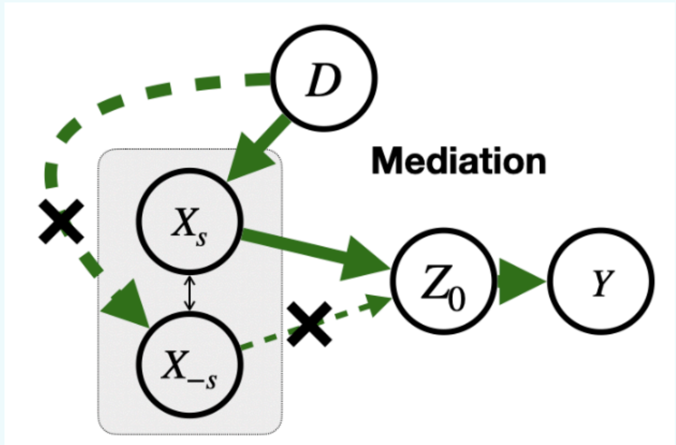
H_0: For all subgroups A with size $\geq \epsilon$, the candidate covariate shift solely with respect to variable subset X_s explains the performance change in A, i.e.

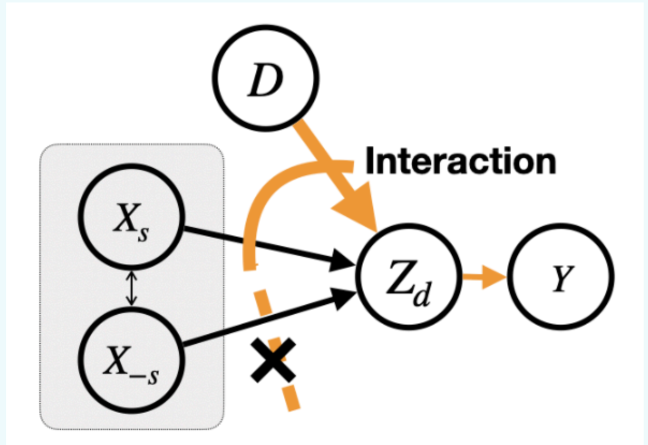
$$\mathbb{E}_1[Z_0(X) \mid X \in A] - \mathbb{E}_s[Z_0(X) \mid X \in A] \leq \tau.$$

X_s-specific Outcome Shift Hypothesis

H_0: For all subgroups A with size $\geq \epsilon$, the candidate outcome shift solely with respect to variable subset X_s explains the performance change in A, i.e.

$$\mathbb{E}_1[Z_1(X) \mid X \in A] - \mathbb{E}_1[Z_s(X) \mid X \in A] \leq \tau.$$





SHIFT step-by-step

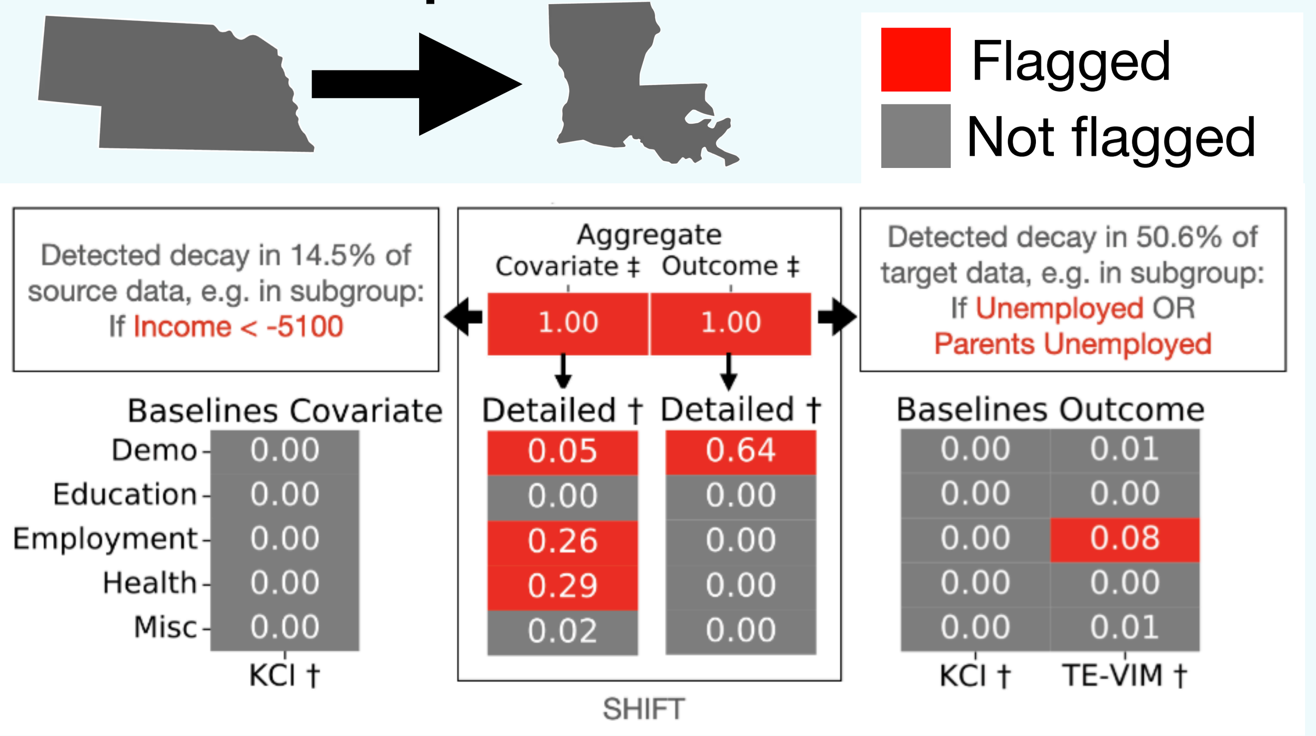
Step 1. Split data into train vs test:

Train		Test
Nuisance Parameters $\hat{Z}_0, \hat{Z}_1, \hat{Z}_s, \hat{\pi}, \hat{\pi}_s$	Candidate subgroups $\hat{A}_{agg}, \hat{A}_s$	Test statistic e.g. $E[(\ell - Z_0(X) - \tau)1\{X \in \hat{A}\}]$

Step 2. Estimate nuisance parameters (outcome and density ratio models) and identify candidate subgroups using ML.

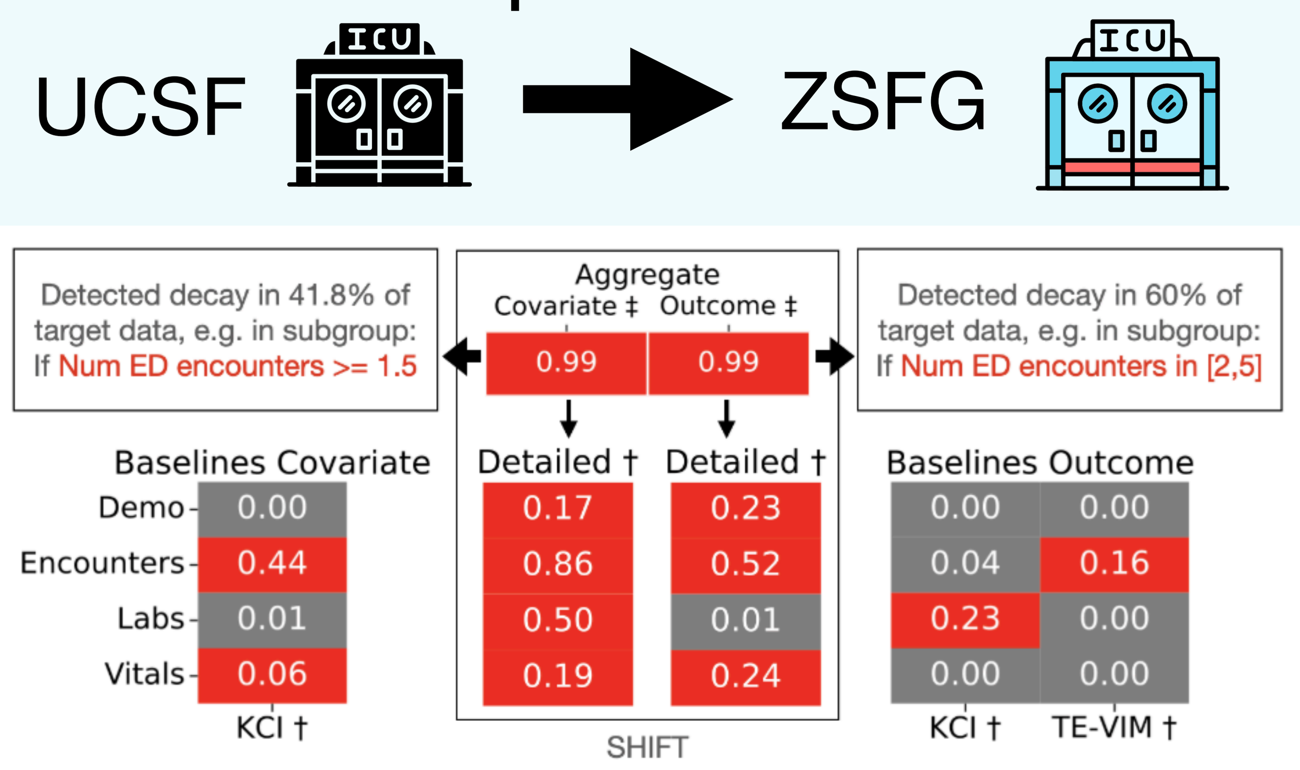
Step 3. Construct test statistics using double-debiased ML. Obtain p-values using multiplier bootstrap.

Experiment: Diagnosing an insurance prediction model



SHIFT flags aggregate tests that are rejected to indicate a subgroup has been detected and flags X_s-specific tests that are *not* rejected as potential explanations.

Experiment: Diagnosing a readmission prediction model



Paper here