Introduction

Counterfactual causal inference requires the assumption of strong ignorability. Observational data typically does not satisfy this assumption. Weighting is a method to enforce strong ignorability, but many weighting methods estimates can be unstable. [1]

The Model. This research proposes a generative adversarial network (GAN)-based model called the Counterfactual χ-GAN (cGAN) to learn stable, feature-balancing weights. [2]

• cGAN utilizes the f-GAN framework to minimize the χ-divergence. [3]
• There is a single generator, G, and two or more variational functions V_a, corresponding to A treatments.

\[ \sum_{a=1}^{\alpha} \chi^2 (p(x) \parallel q_a(x)) \]

N_a units are drawn from an unknown and population-specific distribution q_a. Our objective is to identify a set of weights, w_a, for each population that allow estimation of expectations from the same target distribution, p.

Of Note About the Model
• cGAN uses the variational divergence minimization to optimize the χ-divergence
• G identifies the target distribution that minimizes the sampling variance and encourages coverage
• Weights (w_a) are directly calculated from the output of V_a and enforce the assumption of strong ignorability.

Simulation. To evaluate cGAN, we applied the model to a simulation in which the ground truth is known. Two populations were constructed such that half of each was generated from the same distribution (Subpop A).

• Pop 1 = Subpop A + Subpop B
• Pop 2 = Subpop A + Subpop C

cGAN learned higher weights for units from Subpop A than units not generated from this subpopulation.

Application to Clinical Data. We additionally applied cGAN to a clinical experiment using EHR data from Columbia University Irving Medical Center.

• sitagliptin vs. glimepiride in elderly patients with T2DM

We evaluated cGAN in improving feature balance compared to inverse propensity weighting (IPW), clipped-IPW, using the absolute standardized difference in the means (ASDM)

Experimentation

Simulation Results. Left: Select features (i) by population of origin; (ii) with subpopulation A highlighted; (iii) samples from the generator; (iv) opacity adjusted by weight. Right: Distribution of weights by subpopulation.

<table>
<thead>
<tr>
<th>Method</th>
<th>ASDM</th>
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<tr>
<td>unweighted</td>
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<tr>
<td>IPW</td>
<td>0.0876</td>
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<tr>
<td>clipped-IPW</td>
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<tr>
<td>cGAN</td>
<td>0.0252</td>
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</tbody>
</table>

Figure 1: Simulation Results. Left: Select features (i) by population of origin; (ii) with subpopulation A highlighted; (iii) samples from the generator; (iv) opacity adjusted by weight. Right: Distribution of weights by subpopulation.

Figure 2: ASDM for Clinical Data