

Comparisons of the Treatment and Side Effects of Several Bariatric Surgery Procedures: An Observational Study via Random Forest-based and Neural Network-based Approaches

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Abstract

Motivation: Bariatric surgery is an effective treatment for obesity, diabetes, high blood pressure, sleep apnea, and high cholesterol. Over the past decades, several bariatric surgery procedures based on different techniques have been widely performed. However, there is a lack of rigorous causal comparisons of their treatment and side effects.

Questions: We conduct a large-scale observational study to compare the effects of several widely used bariatric surgery procedures on bariatric surgery complication risk and weight loss using the datasets from the American College of Surgeons Metabolic and Bariatric Surgery Accreditation and Quality Improvement Program (MBSAQIP).

Methods: We apply several state-of-art machine-learning-based causal inference approaches such as Causal Forest, Orthogonal Random Forest, and Dragonnet to leverage the large datasets better to provide accurate and powerful causal comparisons, both at population and individual levels.

Contributions: The results from our population-level causal comparisons provide rigorous statistical evidence for the appropriateness of the current guidelines for bariatric surgery procedures provided by the American Society for Metabolic and Bariatric Surgery (ASMBS).

Variables of Interest

Post-operative outcomes of interest

Primary outcome (surgery effect): BMI difference within 30 days of the procedure

Secondary outcomes (side effect): risk of reoperation, readmission, intervention within the 30 days of the postoperative period

Bariatric surgery types of interest

Sleeve Gastrectomy (Sleeve), Roux-en-Y Gastric Bypass (RYGB), Adjustable Gastric Band (AGB, or Band), Biliopancreatic Diversion with Duodenal Switch (BPD/DS), Single Anastomosis Duodeno-Ileal Bypass with Sleeve Gastrectomy (SADIS)

Preoperative covariates of interest

Gender, Age, Race, ... (31 variables in total)

Notations and Definitions

Let X be all pre-operative variables that affect the post-operative outcomes except the types of surgery; T to be bariatric surgery type (consider 'Sleeve' as control, i.e., $T = 0$ and the other surgery type of interest as treated, i.e., $T = 1$); and Y to the outcome of interest, i.e., BMI difference within 30 days or complication risk.

Average (population) treatment effect (ATE)

$$\tau = \mathbb{E}[Y_i^{(1)}(x) - Y_i^{(0)}(x)]$$

Conditional (individual) treatment effect (CATE)

$$\theta(x) = \mathbb{E}[Y_i^{(1)}(x) - Y_i^{(0)}(x)|X_i = x]$$

Average (population) causal risk ratio

$$\psi_a = \frac{P(Y_i^{(1)}(x) = 1)}{P(Y_i^{(0)}(x) = 1)}$$

Individual (individual) causal risk ratio

$$\psi_c(x) = \frac{P(Y_i^{(1)}(x) = 1|X_i = x)}{P(Y_i^{(0)}(x) = 1|X_i = x)}$$

Methods

Causal Forest

$$\hat{\mu}^{(t)}(x) = \mathbb{E}[Y_i^{(t)}(x)|X_i = x] = \frac{1}{|\{i : T_i = t, X_i \in L(x)\}|} \sum_{\{i: T_i=t, X_i \in L(x)\}} Y_i$$

here $t = 0$ or 1 and L is a set of leaves gained by recursively splitting the feature space, each of which only contains a few training samples.

Orthogonal Random Forest

Solve the moment equation via local orthogonal moments in a two-stage estimation process:

1. Compute a nuisance estimate for \hat{h} with some guarantee on the conditional root mean squared error:

$$\mathcal{E}(\hat{h}) = \sqrt{\mathbb{E} \left[\|\hat{h}(x) - h_0(x)\|^2 | X = x \right]}$$

2. Compute the estimate $\hat{\theta}(x)$ using the nuisance estimate \hat{h} via the plug-in weighted moment condition, i.e. solve $\hat{\theta}(x)$ via

$$\sum_{i=1}^n a_i [Y - \theta_0(x)T - f_0(x)|X = x] = 0$$

where a_i is the ORF weight to each observation i .

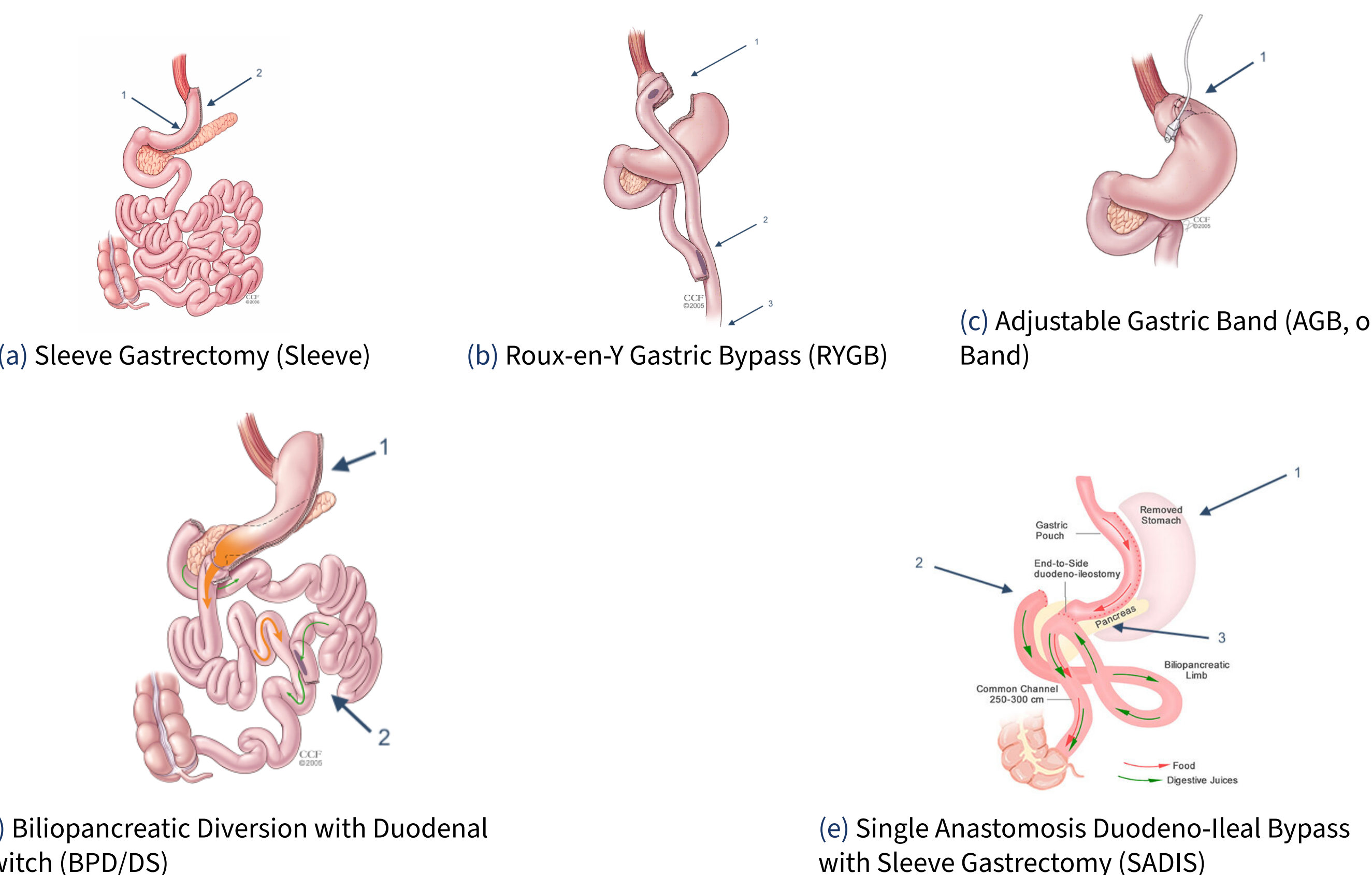
Dragon Net: Adapting Neural Networks for the Estimation of Treatment Effects

Train the model by minimizing the objective function:

$$\hat{\tau} = \arg \min \hat{R}(\tau, X)$$
$$\hat{R}(\tau, X) = \frac{1}{n} \sum_i \left[\hat{y}(t_i, x_i; \tau) - y_i \right]^2 + \alpha \cdot \text{CrossEntropy}(\hat{p}(x_i; \theta), t_i)$$

where \hat{p} is the propensity prediction and α is a hyperparameter weighting the loss component.

Scientific Explanation



Scientific Explanation

Sleeve Gastrectomy (Sleeve):

most widely conducted surgery type; simple and shorter surgery time, effective weight loss; may worsen or cause new onset reflux and heart burn

Roux-en-Y Gastric Bypass (RYGB):

more complex when compared to sleeve gastrectomy or gastric band; reliable and long-lasting weight loss; risk for developing ulcers, small bowel complications and obstruction

Adjustable Gastric Band (AGB, or Band):

lowest risk of complications early after surgery; slower and less weight loss than with other surgical procedures; high rate of re-operation

Biliopancreatic Diversion with Duodenal Switch (BPD/DS):

more complex surgery; best results for improving obesity; slightly higher complication rates than other procedures

Single Anastomosis Duodeno-Ileal Bypass with Sleeve Gastrectomy (SADIS):

simpler and faster to perform than gastric bypass or BPD-DS; newer operation with only short-term outcome data; excellent option for a patient who already had a sleeve gastrectomy and is seeking further weight loss

Numerical Results

We consider **Sleeve as the baseline surgery type** and estimate the treatment effects of other surgery types:

	CF	ORF	DNet(backdoor)	DNet(backdoor reg)	DNet (tmle)	DNet (tmle reg)
RYGB	-0.0339	-0.0512	-0.0341	-0.0327	-0.0340	-0.0340
AGB	-0.773	-0.864	-0.913	-0.866	-0.831	-0.773
BPD/DS	0.352	0.334	0.352	0.382	0.350	0.352
ADIS	-0.531	-0.532	-0.570	-0.570	-0.490	-0.531

We are currently working on the side effects estimation of each surgery types compared with Sleeve.

References

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