Bootstrap-based goodness-of-fit test for parametric regression based on conditional distribution families

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Motivating Example

How does *Y* depend on *X*?

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Which one appropriately models the given data?

 Data : i.i.d. sample of covariates $X_i \in \mathbb{R}^p$ and output variables $Y_i \in \mathbb{R}$

Goal: Find a good model for the conditional distribution $Y|X \sim F$

Method: Test goodness of fit for different parametric families

$$
H_0: F \in \mathcal{F} = \{(x, y) \mapsto F_\vartheta(y|x) \, | \, \vartheta \in \Theta\} \quad \text{vs.} \quad H_1: F \notin \mathcal{F}
$$

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• Other approaches using kernel estimators

- Difference between non-parametric and semi-parametric estimate of *F^Y*
- Non-parametric fit: empirical distribution function (ecdf)

$$
\hat{F}_{Y,n}(t) = \frac{1}{n} \sum_{i=1}^{n} \mathbb{1}_{\{Y_i \le t\}}
$$

 \bullet Semi-parametric fit, using MLE $\hat{\vartheta}_n$ and ecdf \hat{H}_n of $\{X_i\}_{i=1}^n$:

$$
\hat{F}_{Y,\hat{\vartheta}_n}(t) = \int F_{\hat{\vartheta}_n}(t|x) \hat{H}_n(dx) = \frac{1}{n} \sum_{i=1}^n F_{\hat{\vartheta}_n}(t|X_i)
$$

• Conditional empirical process with estimated parameters:

$$
\tilde{\alpha}_n(t) = \sqrt{n} \left(\hat{F}_{Y,n}(t) - \hat{F}_{Y,\hat{\vartheta}_n}(t) \right)
$$

$$
= \frac{1}{\sqrt{n}} \sum_{i=1}^n \mathbb{1}_{\{Y_i \le t\}} - F_{\hat{\vartheta}_n}(t|X_i)
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Find distribution of $\|\tilde{\alpha}_n\|_{\infty}$ to decide when H_0 should be rejected

Theorem

Under *H*⁰ and some regularity conditions, *α*˜*ⁿ* converges weakly to a centered Gaussian process $\tilde{\alpha}_{\infty}$ with known covariance function which is dependent on the true distribution functions of *X* and *Y* .

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Use bootstrap to approximate the distribution of $||\tilde{\alpha}_n||_{\infty}$.

Goal: Estimate the distribution of $\|\tilde{\alpha}_n\|_{\infty}$ under H_0

Method:

- Resample from the given data in a way that H_0 is fulfilled $(Y_i^* \sim F_{\hat{\vartheta}_n}(\cdot | X_i))$
- Compute the test statistic ∥*α*˜ ∗ *ⁿ*∥[∞] for this new sample
- Repeat these steps many times and use the ecdf of the resulting test statistics as an estimate

 ${\sf Usage:}$ $p\text{-value}$ is approximated by the percentage of $\|\tilde{\alpha}^*_n\|_\infty$ that are greater than or equal to ∥*α*˜*n*∥[∞]

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Theorem

Under H_0 and some regularity conditions, $\tilde{\alpha}_n^*$ converges weakly to the same limit process $\tilde{\alpha}$ _∞.

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- Compared to Stute and Zhu [\(2002\)](#page-21-1) / Dikta and Scheer [\(2021\)](#page-21-2): More general because it cannot only be applied for GLMs
- Compared to Andrews [\(1997\)](#page-21-3): Better applicable to cases with high-dimensional covariates
- Compared to all of them: In some cases more sensitive to deviations from H_0

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Thank you for your attention! Any questions? :)