Using Probabilistic Knockoffs of Binary Variables to Control the False Discovery Rate

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Overview

- 1. Original Knockoffs: What They Do and Where They Fail
- 2. Making Knockoffs Work With GLMs
- 3. Random Binary Knockoffs: The Theory
- 4. Random Binary Knockoffs: Performance
- 5. Where to next?

Variable Selection in Linear Regression

Assume

$$\mathbf{y} = X\beta + \mathbf{z}$$

where $\mathbf{y} \in \mathbb{R}^n$, $X \in \mathbb{R}^{n \times p}$, $\beta \in \mathbb{R}^p$, and \mathbf{z} is Gaussian noise. Also, assume sparsity:

$$\beta_i = 0 \quad \forall i \notin S$$

How do we pick estimate \hat{S} ?

False Discover Rate

A common goal for a method that generates $\hat{\mathcal{S}}$ is to control the false discovery rate

$$FDR = E\left[\frac{|\{j: \beta_j = 0 \& j \in \hat{S}\}|}{\max\{|\hat{S}|, 1\}}\right]$$

In other words, control portion of elements in \hat{S} which aren't in S.

FDR is controlled at level q if q <FDR irrespective of true β .

Knockoffs

Knockoff variables can be used to control FDR in linear regression.

- ► The idea is to create a forgery of each variable; if the forgeries seem about as good predictors as the originals, the originals are lousy predictors.
- ▶ For each variable X_i , create a knockoff feature \tilde{X}_i . Such that.

$$\tilde{X}^T \tilde{X} = X^T X$$
 & $X^T \tilde{X} = X^T X - \text{diag}\{\mathbf{s}\}\$

Where $\operatorname{diag}\{X^TX\} - s$ is small but $\operatorname{diag}\{X^TX\} - s \succeq 0$

- \tilde{X}_i and X_i will have same correlation with other variables, but only low correlation with each other.
- Given \mathbf{s} , \tilde{X} can be generated via a rotation of X.

Knockoff Filter

These knockoffs can be used in the knockoff filter method.

▶ Fit full path of LASSO regression on $[X\tilde{X}]$.

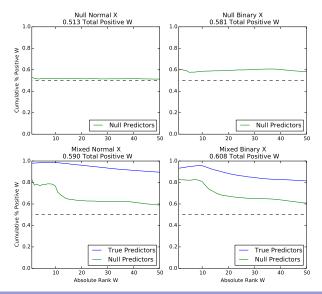
$$\beta(\lambda) = \arg\min_{\mathbf{b}} \left\{ \frac{1}{2} \|\mathbf{y} - X_L \mathbf{b}\|_2^2 + \lambda \|b\|_1 \right\}$$

- ▶ Z_i , \tilde{Z}_i largest λ such that X_i , \tilde{X}_i have nonzero coefficient.
- $W_i = Z_i$ if $Z_i > \tilde{Z}_i$, otherwise $W_i = -\tilde{Z}_i$.
- ▶ Since $[X\tilde{X}]^T[X\tilde{X}]$ & $[X\tilde{X}]^T\mathbf{y}$ sufficient statistics for $\beta(\lambda)$, W_i symmetrically distributed around 0 when X_i null predictor.
- ▶ Thus, FDR controlled when $\hat{S} = \{i : W_i > T\}$ for

$$T = \min \left\{ t > 0 : \frac{|\{j : W_j \le -t\}|}{\max\{|\{j : W_j \ge t\}|, 1\}} \le q \right\}$$

Where Knockoff Filter Fails

Knockoff filter don't work for other GLMs.



Can Knockoffs Be Fixed for GLMs?

- Other GLMs don't have the same sufficient statistics as linear regression.
- Original Knockoffs don't remotely have same distribution as X, so "look" different than real variables.
- Knockoffs will likely work better if they have the same marginal distribution as originals.
- ► For *X_i* with arbitrary distribution, unclear how this might be accomplished.

Random Binary Knockoffs

- Other GLMs don't have the same sufficient statistics as linear regression.
- ▶ Original Knockoffs don't remotely have same distribution as X, so "look" different than real variables.
- Knockoffs will likely work better if they have the same marginal distribution as originals.
- ▶ This would be extremely difficult in the most general case.