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Topic 18: False Discovery Rate (FDR) and Knockoffs

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Key points: Constructing knockoff variables to control FDR when estimating regression coefficients.

Disclaimer: *The note is built on Prof. Jinchi Lv's lectures of the course at USC, DSO 607, High-Dimensional Statistics and Big Data Problems.*

18.1 Motivation

Consider the classical linear regression setting

$$\mathbf{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\epsilon}$$

where $\boldsymbol{\beta} \in \mathbb{R}^p$ is the unknown vector of coefficients and $\boldsymbol{\epsilon} \sim \mathcal{N}(\mathbf{0}, \sigma^2\mathbf{I})$. In a high-dimensional problem, we would like to just select a subset of all variables $\hat{S} \subset \{1, \cdots, p\}$ s.t. conditional on $\{\mathbf{X}_j\}_{j \in \hat{S}}$, $\mathbf{y}$ is **independent** of all other variables, we can define the **False Discovery Rate** **(FDR)** in can be defined as

Definition 18.1.1: False Discovery Rate (FDR)

$$\text{FDR} = \mathbb{E}(\text{FDP}) = \mathbb{E}\left[\frac{|\hat{\mathcal{S}} \cap \mathcal{H}_0|}{|\hat{\mathcal{S}}|} = \frac{\#\{j : j \in \hat{\mathcal{S}} \setminus \mathcal{S}\}}{\#\{j : j \in \hat{\mathcal{S}}\}}\right]$$

where $\mathcal{H}_0 \subset \{1, \cdots, p\}$ is the set of **null** variables: $\mathbf{X}_j$ is **null** iff $\mathbf{Y}$ is independent of $\mathbf{X}_j$ conditional on the other variables $\mathbf{X}_{-j} = \{\mathbf{X}_1, \cdots, \mathbf{X}_p\} \setminus \{\mathbf{X}_j\}$.

In this note, we consider a series of knockoff-based methods to control FDR. They all follow a common procedure:

- **Step 1**: Construct Knockoffs
- **Step 2**: Calculate test statistics for both original and knockoff variables
- **Step 3**: Calculate a threshold for the test statistics, controling for a desired FDR level
- **Step 4**: Select variables that pass the threshold

18.2 Barber and Candes (2015)

Constructing the knockoffs Barber and Candes (2015) construct the knockoffs by the following procedure

- Calculate the Gram matrix $\boldsymbol{\Sigma} = \mathbf{X}'\mathbf{X}$ for the normalized original variables, where $\Sigma_{jj} = \|\mathbf{X}_j\|_2^2 = 1$

- Construct the knockoffs $\tilde{\mathbf{X}}$ s.t.

$$\tilde{\mathbf{X}}'\tilde{\mathbf{X}} = \mathbf{\Sigma} \qquad\qquad \mathbf{X}'\tilde{\mathbf{X}} = \mathbf{\Sigma} - \text{diag}\{\mathbf{s}\}$$

  where $\mathbf{s} \in \mathbb{R}_+^p$ is a p-dimensional non-negative vector (larger s_j indicates higher power) and
  - $\tilde{\mathbf{X}}$ exhibits the **same** covariance structrue as the original design $\mathbf{X}$
  - The correlation between distinct original variables and knockoffs are the same as between the originals:

$$\mathbf{X}_j'\tilde{\mathbf{X}}_k = \mathbf{X}_j'\mathbf{X}_k,\ \forall j \neq k$$

  - The correlation between the original variables and their own knockoffs is **less than 1**

$$\mathbf{X}_j'\tilde{\mathbf{X}}_j = \Sigma_{jj} - s_j = 1 - s_j$$

  To construct such knockoffs,
  - Given a proper $\mathbf{s}$, if $n \geq 2p$, then

$$\tilde{\mathbf{X}} = \mathbf{X}(\mathbf{I} - \mathbf{\Sigma}^{-1}\text{diag}\{\mathbf{s}\}) + \tilde{\mathbf{U}}\mathbf{C}$$

    where $\tilde{\mathbf{U}} \in \mathbb{R}^{n\times p}$ is an **orthonormal** matrix s.t. $\tilde{\mathbf{U}}'\mathbf{X} = \mathbf{0}$ and $\mathbf{C}'\mathbf{C} = 2\text{diag}\{\mathbf{s}\} - \text{diag}\{\mathbf{s}\}\mathbf{\Sigma}^{-1}\text{diag}\{\mathbf{s}\} \geq \mathbf{0}$
  - A sufficient and necessary condition for $\tilde{\mathbf{X}}$ to exist: $\text{diag}\{\mathbf{s}\} \leq 2\mathbf{\Sigma}$

  2 types of knockoffs can be constructed, following these procedures

  T1 **Equi-correlated** knockoffs: set $s_j = 2\lambda_{\min}(\mathbf{\Sigma}) \wedge 1$ for all j, then $\langle \mathbf{X}_j, \tilde{\mathbf{X}}_j\rangle = 1 - 2\lambda_{\min}(\mathbf{\Sigma}) \wedge 1$ for all j. This is essentially minimizing $\left|\langle \mathbf{X}_j, \tilde{\mathbf{X}}_j\rangle\right|$

  T2 **SDP** knockoffs: solve the convex problem

$$\arg\min_{\mathbf{x}} \sum_j (1 - s_j) \qquad\qquad s.t. 0 \leq s_j \leq 1, \text{diag}\{\mathbf{s}\} \leq 2\mathbf{\Sigma}$$

  which is essentially minimizing the average of $\langle \mathbf{X}_j, \tilde{\mathbf{X}}_j\rangle$

Calculate test statistics Define and calculate test statistics W_j for each $\beta_j \in \{1, \cdots, p\}$ using $\begin{bmatrix}\mathbf{X} & \tilde{\mathbf{X}}\end{bmatrix}$:

- the test statistic W_j should be constructed s.t. large positive values are evidence against the null hypothesis $\beta_j = 0$, for example, consider a Lasso on $\begin{bmatrix}\mathbf{X} & \tilde{\mathbf{X}}\end{bmatrix}$

$$\hat{\beta}(\lambda) = \arg\min_{\mathbf{b}} \left\{\frac{1}{2}\left\|\mathbf{y} - \begin{bmatrix}\mathbf{X} & \tilde{\mathbf{X}}\end{bmatrix}\mathbf{b}\right\|_2^2 + \lambda \left\|\mathbf{b}\right\|\right\}_1$$

  where λ is the point on the Lasso path at which the feature enters the model as

$$Z_j = \sup\left\{\lambda : \hat{\beta}_j(\lambda) \neq 0\right\}$$

  and set $W_j = (Z_j \vee \tilde{Z}_j) \cdot \begin{cases} +1, & Z_j > \tilde{Z}_j \\ -1, & Z_j < \tilde{Z}_j \end{cases}$ [1]

- In general, the statistics W should satisfy the **sufficient** property and **anti-symmetry** property:

[1] Other choices of W_j are $W_j = \left|\mathbf{X}_j'\mathbf{y}\right| - \left|\tilde{\mathbf{X}}_j'\mathbf{y}\right|$, or $\left|\hat{\beta}_j^{\text{LS}}\right| - \left|\hat{\beta}_{j+p}^{\text{LS}}\right|$

Definition 18.2.1: Property of Test Statistics W_j

The test statistic W_j is said to obey

– the **sufficient** property if $\mathbf{W}$ depends *only* on the Gram matrix and on feature-response inner products, that is

$$\mathbf{W} = f\left([\mathbf{X} \quad \tilde{\mathbf{X}}]' [\mathbf{X} \quad \tilde{\mathbf{X}}], [\mathbf{X} \quad \tilde{\mathbf{X}}]' \mathbf{y} \right)$$

– the **antisymmetry** property if swapping the original $\mathbf{X}_j$ and its knockoff $\tilde{\mathbf{X}}_j$ has the effect of **switching the sign** of W_j, that is

$$W_j(Z_j, \tilde{Z}_j) = -W_j(\tilde{Z}_j, Z_j)$$

Calculate a threshold for the test statistics After defining the test statistic, we then

- Let q be the target FDR, define the data-dependent threshold T as

$$T = \min\left\{ t \in \mathcal{W} : \frac{\#\left\{j : W_j \leq -t\right\}}{\#\left\{j : W_j \geq t\right\} \vee 1} \leq q \right\}$$

where $\mathcal{W} = \left\{ \left|W_j\right| : j = 1, \cdots, p \right\} \setminus \{0\}$ is the set of unique non-zero values attained by $|W_j|$'s.

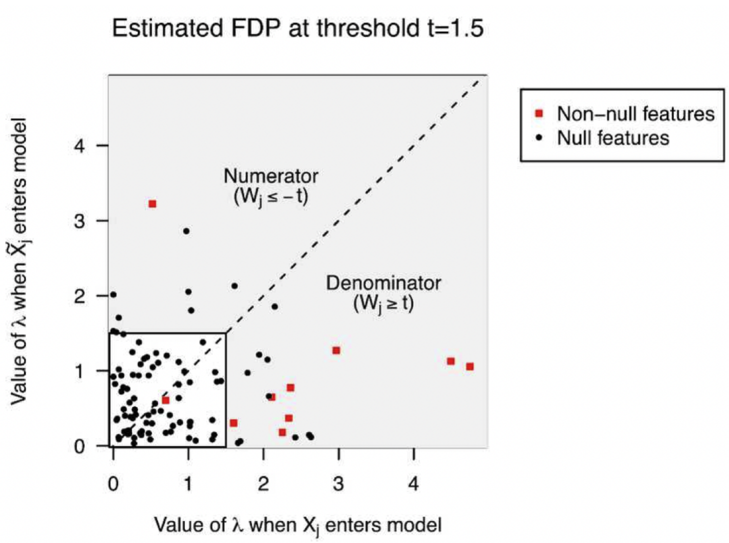

Figure 18.1: Visualizing Test Statistic Thresholding

Variable selection after building the threshold,

- for each $j = 1, \cdots, p$, reject $H_{0,j} : \beta_j = 0$ if $W_j \geq T$, the knockoff filter selects the model

$$\hat{S} = \left\{ j : W_j \geq T \right\}$$

18.2.1 Intuition and Theory

Why knockoffs work?

- **W** is constructed (**antisymmetry** and **sufficiency**) such that the signs of the W_j's are i.i.d. random for the null
- for any threshold t, we have

$$\#\left\{j : \beta_j = 0, W_j \geq t\right\} \stackrel{d}{=} \#\left\{j : \beta_j = 0, W_j \leq -t\right\}$$

, and the false discovery proportion (FDP) can be estimated as

$$\begin{aligned}\frac{\#\left\{j : \beta_j = 0, W_j \geq t\right\}}{\max\left(\#\left\{j : W_j \geq t\right\}, 1\right)} &\simeq \frac{\#\left\{j : \beta_j = 0, W_j \leq -t\right\}}{\max\left(\#\left\{j : W_j \geq t\right\}, 1\right)} \\ &\leq \frac{\#\left\{j : W_j \leq -t\right\}}{\max\left(\#\left\{j : W_j \geq t\right\}, 1\right)} := \widehat{\mathrm{FDP}}(t)\end{aligned}$$

then the knockoff procedure can be interpreted as finding a threshold via $T = \min\left\{t \in \mathcal{W} : \widehat{\mathrm{FDR}}(t) \leq q\right\}$

The knockoff procedure essentially controls a quantity **nearly equal** to the FDR. To control the FDR **exactly**, we have, textbfknockoff+ , a more conservative modification of the knockoff procedure, where the threshold is

$$T = \min\left\{t \in \mathcal{W} : \frac{1+\#\left\{j : W_j \leq -t\right\}}{\max\left(\#\left\{j : W_j \geq t\right\}, 1\right)} \leq q\right\}$$

the $+1$ part makes it harder to reject the null:

$$\begin{aligned}\mathrm{FDP} &= \frac{\#\left\{j : \beta_j = 0, W_j \geq -T\right\}}{\#\left\{j : W_j \geq T\right\} \vee 1} \cdot \frac{1 + \#\left\{j : \beta_j = 0, W_j \leq -T\right\}}{1 + \#\left\{j : \beta_j = 0, W_j \leq -T\right\}} \\ &\leq \frac{1 + \#\left\{j : W_j \leq -T\right\}}{\#\left\{j : W_j \geq T\right\} \vee 1} \cdot \frac{\#\left\{j : \beta_j = 0, W_j \geq T\right\}}{1 + \#\left\{j : \beta_j = 0, W_j \leq -T\right\}} \\ &\leq q \cdot 1\end{aligned}$$

Then, we have the following theorem

Theorem 18.2.2: Property of the Knockoff Method

For any $q \in [0, 1]$, the **knockoff** method satisfies

$$\mathbb{E}\left[\frac{\#\left\{j : \beta_j = 0, j \in \hat{S}\right\}}{\#\left\{j : j \in \hat{S}\right\} + q^{-1}}\right] \leq q$$

and the **knockoff+** method satisfies

$$\mathbb{E}\left[\frac{\#\left\{j : \beta_j = 0, j \in \hat{S}\right\}}{\#\left\{j : j \in \hat{S}\right\}}\right] \leq q$$

in both cases, teh expectation is taken over the Gaussian noise in the model, while treating original variables $\mathbf{X}$ and knockoffs $\tilde{\mathbf{X}}$ as fixed

18.3 Candes et al. (2018)

Another way of constructing knockoffs, introduced by Candès et al. (2018), is by a swapping method:

Constructing the knockoffs for the family of random variables $\mathbf{X} = (\mathbf{X}_1, \cdots, \mathbf{X}_p)$ are a new family of random variables $\tilde{\mathbf{X}} = (\tilde{\mathbf{X}}_1, \cdots, \tilde{\mathbf{X}}_p)$ constructed with the following 2 properties

- for any subset $S \subset \{1, \cdots, p\}$,
$$(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)} \overset{\text{d}}{=} (\mathbf{X}, \tilde{\mathbf{X}})$$
- $\tilde{\mathbf{X}} \perp\!\!\!\perp \mathbf{Y} \mid \mathbf{X}$ if there is a response $\mathbf{Y}$

Suppose $\mathbf{X} \sim \mathcal{N}(0, \mathbf{\Sigma})$, then $(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)}$ satisfies $(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)} \overset{\text{d}}{=} (\mathbf{X}, \tilde{\mathbf{X}})$ if

$$(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)} \overset{\text{d}}{=} (\mathbf{X}, \tilde{\mathbf{X}}) \sim \mathcal{N}(0, \mathbf{G}), \qquad \text{where } \mathbf{G} = \begin{pmatrix} \mathbf{\Sigma} & \mathbf{\Sigma} - \text{diag}(s) \\ \mathbf{\Sigma} - \text{diag}(s) & \mathbf{\Sigma} \end{pmatrix}$$

where $\text{diag}(s)$ is any **diagonal matrix** s.t. G is **positive semidefinite**. The knockoffs constructed this way are named **MX knockoffs**. For $\mathbf{P}$, the permutation matrix encoding the swap,

$$\mathbf{PGP} = \mathbf{G}$$

then we can sample the knockoff vector $\tilde{\mathbf{X}}$ from the conditional distribution

$$\tilde{\mathbf{X}} \mid \mathbf{X} \overset{\text{d}}{=} \mathcal{N}(\mu, \mathbf{V})$$

where

$$\begin{aligned} \mu &= \mathbf{X} - \mathbf{X}\mathbf{\Sigma}^{-1}\text{diag}(s) \\ \mathbf{V} &= 2\text{diag}(s) - \text{diag}(s)\mathbf{\Sigma}^{-1}\text{diag}(s) \end{aligned}$$

An important lemma is

Lemma 18.3.1: MX Knockoff Construction

For **MX knockoffs**, swapping **null** covariates with their knockoffs would **not** change the joint distribution of the original covariate $\mathbf{X}$ and their knockoffs $\tilde{\mathbf{X}}$, conditional on the repsonse $\mathbf{Y}$: Take any subset $S \subset \mathcal{H}_0$ of nulls, then

$$(\mathbf{X}, \tilde{\mathbf{X}}) \mid \mathbf{y} \overset{\text{d}}{=} (\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)} \mid \mathbf{y}$$

Here, the main assumption of model-X knockoffs is assuming **known** joint distribution of covariates, and this leads to

Proposition 18.3.2: Conditional Exchangeability of MX Knockoffs

The random variables $(\tilde{\mathbf{X}}_1, \cdots, \tilde{\mathbf{X}}_p)$ are **MX knockoffs** for $(\mathbf{X}_1, \cdots, \mathbf{X}_p)$ if and only if for any $j \in \{1, \cdots, p\}$, the pair $(\mathbf{X}_j, \tilde{\mathbf{X}}_j)$ is **exchangeable** conditional on all the other variables and their knockoffs.

under Prop.18.3.2, we can use the following algorithm to construct the MX Knockoffs

Algorithm 18.3.3: Sequential Conditional Independent Pairs

$j = 1$
while $j \le p$ **do**
  sample $\tilde{\mathbf{X}}_j$ from $\mathcal{L}(\mathbf{X}_j \mid \mathbf{X}_{-j}, \tilde{\mathbf{X}}_{1:j-1})$
  $j = j + 1$
end[a]

[a]Example with $p = 3$
- $j = 1$: sample $\tilde{\mathbf{X}}_1$ from $\mathcal{L}(\mathbf{X}_1 \mid \mathbf{X}_{2:3})$
- $j = 2$: sample $\tilde{\mathbf{X}}_2$ from $\mathcal{L}(\mathbf{X}_2 \mid \mathbf{X}_1, \mathbf{X}_3, \tilde{\mathbf{X}}_1)$
- $j = 3$: sample $\tilde{\mathbf{X}}_3$ from $\mathcal{L}(\mathbf{X}_3 \mid \mathbf{X}_{1:2}, \tilde{\mathbf{X}}_{1:2})$

And an **approximate** construction can be achieved via matching the first 2 moments of $(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap(S)}}$ and $(\mathbf{X}, \tilde{\mathbf{X}})$,

$$\operatorname{cov}(\mathbf{X}, \tilde{\mathbf{X}}) = \mathbf{G} \qquad \mathbf{G} = \begin{pmatrix} \mathbf{\Sigma} & \mathbf{\Sigma} - \operatorname{diag}(s) \\ \mathbf{\Sigma} - \operatorname{diag}(s) & \mathbf{\Sigma} \end{pmatrix}$$

which can be achieved through 2 ways:

- **equicorrelated** construction

  $$s_j^{\text{EQ}} = 2\lambda_{\min}(\mathbf{\Sigma}) \wedge 1, \ \forall j$$

  minimizing the **correlation between variable knockoff pairs** subject to the constraint that all such pairs *must have the same correlation*.

  ISSUE with large p: $\lambda_{\min}(\mathbf{\Sigma})$ tends to be extremely small: computationally easy, but **low power** of s_j^{EQ}
- **semidefinite programme** construction

  $$\begin{array}{ll} \text{minimize} & \sum_j \left|1 - s_j^{\text{SDP}}\right| \\ \text{subject to} & s_j^{\text{SDP}} \ge 0, \ \operatorname{diag}\left(s^{\text{SDP}}\right) \preceq 2\mathbf{\Sigma} \end{array}$$

  minimizing the **sum of the absolute values** of variable knockoff correlations between *all* suitable s

  ISSUE with large p: SDP (a convex problem) is computationally expensive

Hence, in high-dimensional situation, follow a 2-step procedure to combine both

- Step 1: choose an **approximation** $\mathbf{\Sigma}_{\text{approx}}$ of $\mathbf{\Sigma}$ and solve

  $$\begin{array}{ll} \text{minimize} & \sum_j \left|1 - \hat{s}_j\right| \\ \text{subject to} & \hat{s}_j \ge 0, \ \operatorname{diag}\left(\hat{s}_j\right) \preceq 2\mathbf{\Sigma}_{\text{approx}} \end{array}$$

- Step 2: solve

  $$\begin{array}{ll} \text{maximize} & \gamma \\ \text{subject to} & \operatorname{diag}\left(\gamma \hat{s}\right) \preceq 2\mathbf{\Sigma} \end{array}$$

  and set $s^{\text{ASDP}} = \gamma \hat{s}$

It's easy to see that this 2-step procedure can be reduced to equicorrelated or semidefinite programme

- **equicorrelated**: $\mathbf{\Sigma} = \mathbf{I} \Rightarrow \hat{s}_j = 1, \gamma = 2 \times \lambda_{\min}\mathbf{\Sigma} \wedge 1$
- **semidefinite programme**: $\mathbf{\Sigma} = \mathbf{\Sigma}, \hat{s}_j = s^{\text{SDP}}, \gamma = 1$

Calculate test statistics After constructing the knockoffs, we can construct the feature importance statistics by imposing a **flip sign** property: swapping the jth variable with its knockoff has the effect of changing the sign of W_j

$$w_j \left\{(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)}, \mathbf{y}\right\} = \begin{cases} w_j \left\{(\mathbf{X}, \tilde{\mathbf{X}}), \mathbf{y}\right\}, & j \notin S \\ -w_j \left\{(\mathbf{X}, \tilde{\mathbf{X}}), \mathbf{y}\right\}, & j \in S \end{cases}$$

consider a statistic $\mathbf{T}$ for each original and knockoff variable

$$\mathbf{T} \triangleq (\mathbf{Z}, \tilde{\mathbf{Z}}) = (Z_1, \cdots, Z_p, \tilde{Z}_1, \cdots, \tilde{Z}_p) = t\left\{(\mathbf{X}, \tilde{\mathbf{X}}), \mathbf{y}\right\}$$

if the components of $\mathbf{T}$ are switched in the same way:

$$(\mathbf{Z}, \tilde{\mathbf{Z}})_{\text{swap}(S)} = t\left\{(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)}, \mathbf{y}\right\}$$

then the **flip sign** property can be achieved by setting

$$W_j = f_j(Z_j, \tilde{Z}_j)$$

where f_j is any **antisymmetric** function $f(v, u) = -f(u, v)$.

Lemma 18.3.4: Feature Statistics: Lasso Coefficient Difference (LCD)

Consider the Lasso **augmented with knockoffs**

$$\min_{b \in \mathbb{R}^{2p}} \frac{1}{2}\|y - (\mathbf{X}, \tilde{\mathbf{X}})b\|_2^2 + \lambda\|b\|_1$$

which has solution $\hat{b}(\lambda) = (\hat{b}_1(\lambda), \cdots, \hat{b}_p(\lambda), \hat{b}_{p+1}(\lambda), \cdots, \hat{b}_{2p}(\lambda))$, then the statistic can be constructed as

$$W_j = Z_j - \tilde{Z}_j = |\hat{b}_j(\lambda)| - |\hat{b}_{j+p}(\lambda)|$$

and conditional on $\left(|W_1|, \cdots, |W_p|\right)$, the sign of the null W_js ($j \in \mathcal{H}_0$) are i.i.d. coin flips[a].

[a]Proof: for a sequence independent random variables $\boldsymbol{\epsilon} = (\epsilon_1, \cdots, \epsilon_p)$ s.t. $\epsilon_j = \pm 1$ with probability $\frac{1}{2}$ if $j \in \mathcal{H}_0$, and $\epsilon_j = 1$ otherwise, put $S = \left\{j : \epsilon_j = -1\right\} \subset \mathcal{H}_0$

- flip sign property: $W_{\text{swap}(S)} \triangleq w\left\{(\mathbf{X}, \tilde{\mathbf{X}})_{\text{swap}(S)}, \mathbf{y}\right\} \boxed{\overset{\text{d}}{=}} \boldsymbol{\epsilon} \odot W = (\epsilon_1 W1, \cdots, \epsilon_p W_p)$
- Lemma 18.3.1: $W_{\text{swap}(S)} \overset{\text{d}}{=} W$

which establishes $W \overset{\text{d}}{=} \boldsymbol{\epsilon} \odot W$

- a large positive value of W_j provides some evidence that the distribution of $\mathbf{Y}$ depends on $\mathbf{X}_j$
- value of λ can be chosen in any data-dependent fashion for a pair of $\mathbf{y}$ and $(\mathbf{X}, \tilde{\mathbf{X}})$

Why **i.i.d. coin flips**? the null W_js are **symmetric**

$$\#\left\{j : W_j \le -t, j \in \mathcal{H}_0\right\} \overset{\text{d}}{=} \#\left\{j : W_j \ge t, j \in \mathcal{H}_0\right\}$$

and for any fixed threshold $t > 0$

$$\#\left\{j : W_j \le -t\right\} \ge \#\left\{j : W_j \le -t, j \in \mathcal{H}_0\right\}$$

so for the false discovery proportion (FDP)

$$\mathrm{FDP}(t) = \frac{\#\left\{j : W_j \ge t, j \in \mathcal{H}_0\right\}}{\#\left\{j : W_j \ge t\right\}}$$

an **upward-biased** estimate is

$$\widehat{\mathrm{FDP}}(t) = \frac{\#\left\{j : W_j \le -t\right\}}{\#\left\{j : W_j \ge t\right\}}$$

then Theorem 18.2.2 applies.

18.4 Fan et al. (2020)

The model-X knockoff (Candès et al., 2018) can accomodate an arbitrarily large p, but assumes **known** joint distribution of covariates. Fan et al. (2020) introduced a data-splitting procedure to separately estimate the unknown covariate distribution and then globally construct the knockoff variables.

Regularity conditions for MX knockoffs Under the conditions

- the components of ϵ are i.i.d. with sub-Gaussian distribution
- $\min_{j \in \mathcal{S}_i} \left|\beta_{0,j}\right| \ge k_n \left(\log(p)/n\right)^{1/2}$ for some slowly diverging sequence $k_n \xrightarrow{n\to\infty} \infty$: Lasso solution does not miss many important features
- $\exists c \in \left(\frac{2}{qs}, 1\right)$ s.t. with asymptotic probability 1, $\left|\hat{\mathcal{S}}\right| \ge cs$ for $\hat{\mathcal{S}} = \left\{1 \le j \le p : W_j \ge T\right\}$: lower bound on the size of the sparse model

then we have

Theorem 18.4.1: Oracle Property of the MX Knockoff Procedure

Under the 3 conditions, all eigenvalues of $\mathbf{\Omega}_0$ are bounded away from 0 and ∞, the smallest eigenvalue of $2\mathrm{diag}(s) - \mathrm{diag}(s)\mathbf{\Omega}_0\mathrm{diag}(s) > 0$ is bounded away from 0, $\lambda = C\sqrt{\log p/n}$ with $C > 0$. Then, the oracle MX knockoffs procedure satisfies that with probability at least $1 - c_3 p^{-c_3}$:

$$\mathrm{Power}(\hat{\mathcal{S}}) = \mathbb{E}\left[\frac{\left|\hat{\mathcal{S}} \cap \mathcal{S}_0\right|}{|\mathcal{S}_0|}\right] \ge 1 - C_{l_1} C_\lambda (\phi + 1) k_n^{-1} - c_3 p^{-c_3} + o(k_n^{-1}) \xrightarrow{n\to\infty} 1$$

where ϕ is the golden ratio and C_{l_1} is some positive constant.

The oracle MX knockoffs procedure in knowing the true precision matrix $\mathbf{\Omega}_0$ for the covariate distribution can indeed have asymptotic power one.

RANK inference procedure The RANK inference procedure is

S1 Randomly split data $(\mathbf{X}, \mathbf{y})$ into two folds each of sample size $n/2$

S2 Use $(\mathbf{X}^{(1)}, \mathbf{y}^{(1)})$ to obtain $\hat{\boldsymbol{\Omega}}$ and a reduced model with support $\tilde{\mathcal{S}}$

S3 Construct knockoffs matrix $\hat{\mathbf{X}} = \mathbf{X}^{(2)}(C^{\hat{\boldsymbol{\Omega}}})' + ZB^{\hat{\boldsymbol{\Omega}}}$ with Z an $\frac{n}{2} \times p$ matrix with i.i.d. $\mathcal{N}(0,1)$ components

S4 Construct $W_j = W_j(\mathbf{y}^{(2)}, \mathbf{X}^{(2)}_{\tilde{\mathcal{S}}}, \mathbf{X}_{\tilde{\mathcal{S}}})$ for $j \in \tilde{\mathcal{S}}$

S5 Apply knockoff inference procedure to W_j's to obtain final set of features $\hat{\mathcal{S}}$

Implementing this modified procedure, we limit ourselves to sparse models $\tilde{\mathcal{S}}$ with size bounded by some positive integer K_n that diverges with n. Fan et al. (2020) also provide theoretical proofs for the robustness of the FDR control and the power of RANK:

$$\text{Power}\left(\hat{\boldsymbol{\Omega}}, \hat{\mathcal{S}}\right) \geq 1 - C_{l_1} C_\lambda (\phi + 1) k_n^{-1} - c_2 p^{-c_2} - c_3 p^{-c_3} + o(k_n^{-1}) = 1 - o(1)$$

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