

A Selective Inference-based Two-stage Procedure for Clinical Safety Studies

Yalin Zhu

Department of Mathematical Sciences
New Jersey Institute of Technology

`yalin.zhu@outlook.com`

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Examples for Multiple Testing

- Evaluating **efficacy** of a new drug for multiple endpoints.
- Detecting **adverse events** across body system in drug safety analysis.
- Selecting **voxels** on multiple brain regions in fMRI studies.

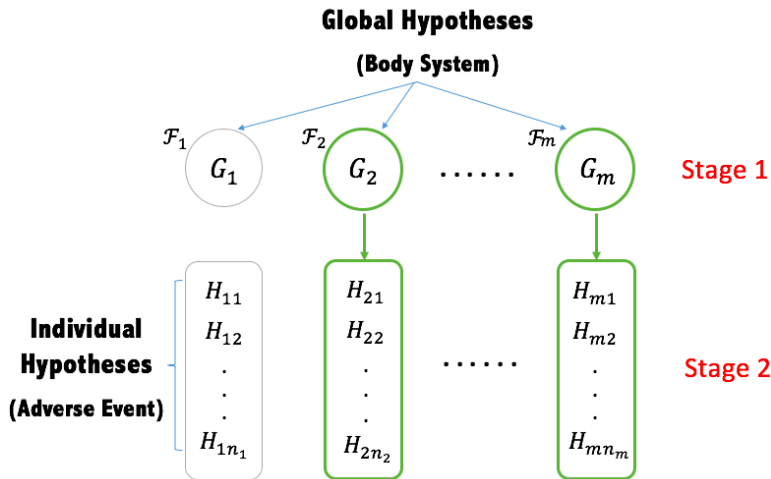
Multiple families/groups structure are often seen in these experiments!

A Motivating Example from Clinical Safety Analysis

- m body systems BS_1, \dots, BS_m .
- n_i adverse event types AE_1, \dots, AE_{n_i} in the BS_i .
- Goal: **Select** Body Systems of Interest (BSol).
Flag significant AEs in BSol.
- Hypothesis: **Family (BS) level** $G_i : \bigcap_{j=1}^{n_i} H_{ij}$ vs. $G'_i : \bigcup_{j=1}^{n_i} H'_{ij}$.
Individual (AE) level $H_{ij} : \theta_{1ij} = \theta_{2ij}$ vs. $H'_{ij} : \theta_{1ij} \neq \theta_{2ij}$.

This safety analysis question can be formulated as a multiple testing problem for multiple families structure!

Addressing Selective Inference



- 1 **Selection:** Body Systems of Interest (BSol)
- 2 **Inference:** Flagging AEs

- A common two-stage procedure uses the same data for both **selection** and **testing**.
- The selection bias leads to the existing multiple testing procedures in clinical safety studies such as *double FDR* and *modified double FDR* failing to strongly control FDR.
- Most existing approaches for multiple families structure multiple testing only consider **individual hypotheses level** error control, but ignore **family level** error control. *It is natural to consider simultaneously controlling error rates for both levels*

- **Family-wise Error Rate:** $FWER = Pr\{\text{reject at least one true null}\}$
 - FWER is suitable for **small scale multiple testing**.
- **Generalized Family-wise Error Rate:**
 $k\text{-FWER} = Pr\{\text{reject at least } k \text{ true nulls}\}$
 - $k\text{-FWER}$ is suitable for **moderate scale multiple testing**.
- **False Discovery Rate:** $FDR = E \left\{ \frac{\# \text{ of rejected true nulls}}{\# \text{ of rejected all hypotheses}} \right\}$
 - FDR is suitable for **large scale multiple testing**.

Stepwise Multiple Testing Procedures (MTPs)

Ordered p -value based stepwise MTP, which is described by using a sequence of non-decreasing critical constants $\alpha_1 \leq \dots \leq \alpha_m$.

- **k -FWER Controlling MTPs**

- Generalized Bonferroni procedure: $\alpha_i = \frac{k\alpha}{m}$
- Generalized Sidak procedure: α_i satisfies $\sum_{j=k}^m \binom{m}{j} \alpha_i^j (1 - \alpha_i)^{m-j} = \alpha$

- **FDR Controlling MTPs**

- **Step-up:** Benjamini-Hochberg (BH) procedure: $\alpha_i = \frac{i\alpha}{m}$
Reject H_i if $p_i \leq \frac{R}{m}\alpha$, where $R = \max\{1 \leq i \leq m : p_{(i)} \leq \frac{i\alpha}{m}\}$.

Problem Formulation

For family index $i = 1, \dots, m$; individual index $j = 1, \dots, n_i$,

- \tilde{p}_i : p -value for the corresponding global hypothesis G_i .
 - \tilde{V} : number of false selections when selecting families.
 - $\mathcal{S} \subseteq \{1, \dots, m\}$: set of selected families.
 - $|\mathcal{S}|$: the number of total selections.
-
- p_{ij} : p -value for the corresponding individual hypothesis H_{ij} .
 - V_i : number of false rejections for i -th family.
 - R_i : number of total rejections for i -th family.

Error Rates Guaranteed in This Work

- **Generalized FWER:** (across families)

$$k\text{-FWER} = Pr\{\tilde{V} \geq k\}$$

- **Conditional FDR for i -th family:** (within families)

$$cFDR_i = E \left\{ \frac{V_i}{R_i \vee 1} \mid i \in \mathcal{S} \right\}.$$

- **Average FDR over selected families:** (overall)

$$\text{average-FDR} = E \left\{ \frac{\sum_{i \in \mathcal{S}} \frac{V_i}{R_i \vee 1}}{|\mathcal{S}| \vee 1} \right\}$$

① Selective (Post-selection) Inference

- Benjamini, Yekutieli (2005) False Discovery Rate: Adjusted Multiple Confidence Intervals for Selected Parameters. *JASA* 100(469):71-81.
- Fithian, Sun, Taylor (2015) Optimal inference after model selection. arXiv:1410.2597.
- Lee, Sun, Sun, Taylor (2013) Exact post-selection inference with the lasso. arXiv:1311.6238.

② Multiple Families Multiple Testing

- Hu et al. (2010) False discovery rate control with groups. *JASA* 105(491):1215-27.
- Benjamini, Bogomolov (2014) Selective inference on multiple families of hypotheses. *JRSSB* 76(1):297-318.
- Heller et al. (2016) Post-selection inference following aggregate level hypothesis testing in large scale genomic data. bioRxiv:058404.

A Selective Inference-Based Two-Stage Procedure

Procedure 1 (cFDR- α -minP-k-Sidak- α_1)

- 1 (a) For each body system, compute the global p-value $\tilde{p}_i = n_i \min_{1 \leq j \leq n_i} \{p_{ij}\}$.
- (b) Apply generalized Sidak procedure on $\tilde{p}_1, \dots, \tilde{p}_m$ at level α_1 .
- 2 (a) In the i -th selected body system, calculate the conditional p-value for H_{ij} :
$$p'_{ij} = \frac{p_{ij}}{t_i} \text{ if } \min_{1 \leq s \leq n_i, s \neq j} \{p_{is}\} > t_i; \text{ otherwise, } p'_{ij} = p_{ij}, \text{ where}$$
$$t_i = 1 - (1 - \tilde{t})^{\frac{1}{n_i}}.$$
- (b) Apply BH procedure on $p'_{i1}, \dots, p'_{in_i}$ at level α .

Several Remarks

- 1 The selection rule: $\tilde{p}_i \leq \tilde{t}$ is equivalent to minP combining function $f(p_{i1}, \dots, p_{in_i}) = \min_{1 \leq j \leq n_i} \{p_{ij}\} \leq t_i$.
- 2 The conditional p -value is inflated from original p -value, $P'_{ij} := P_{ij} | \min\{p_{i1}, \dots, p_{ij-1}, P_{ij}, p_{ij+1}, \dots, p_{in_i}\} \leq t_i = \frac{P_{ij}}{b_{ij}}$, then observed $p'_{ij} = p_{ij}/b_{ij}$, where the inflation factor
$$b_{ij} = \begin{cases} t_i & \text{if } \min_{1 \leq s \leq n_i, s \neq j} \{p_{is}\} > t_i, \\ 1 & \text{otherwise.} \end{cases}$$
- 3 If the individual p -value $p_{ij} \sim U(0, 1) \rightarrow$ the conditional p -value $p'_{ij} \sim U(0, 1)$

Error Rates Control

Theorem 1 (k -FWER control)

If global p -values $\tilde{P}_1, \dots, \tilde{P}_m$ are independent p -values with $U(0, 1)$ under true null, then Procedure 1 strongly controls the k -FWER at level α_1 across body systems.

Theorem 2 (cFDR control)

For each selected body system \mathcal{F}_i , if individual p -values P_{i1}, \dots, P_{in_i} are independent p -values with $U(0, 1)$ under true null, then Procedure 1 strongly controls the conditional FDR at level α .

Corollary 1 (average-FDR control)

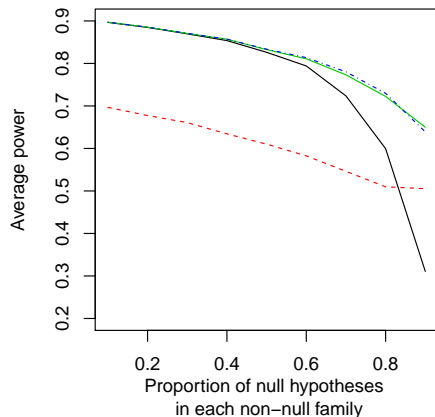
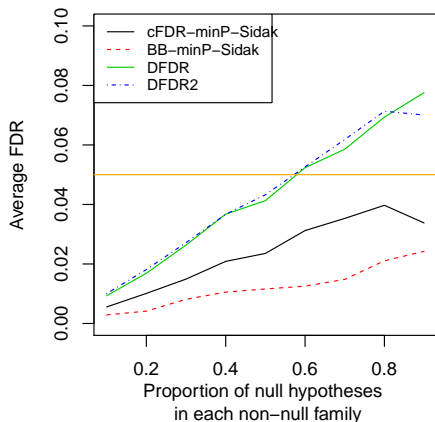
Under the assumption of Theorem 1 and 2, Procedure 1 strongly controls the average FDR at level α .

Simulation Settings I: Independence

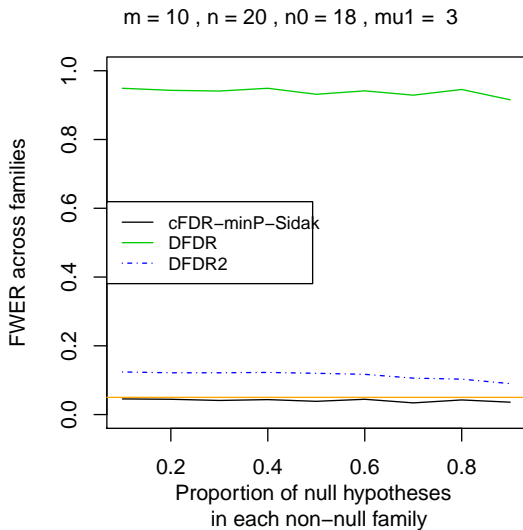
- m : number of BS; n : number of AE.
- Generate $m \times n$ independent normal r.v. matrix with $X_{ij} \sim N(\mu_{ij}, 1)$, where $i = 1, \dots, m; j = 1, \dots, n$.
- $m = 10, n = 20, m_0 = \{2, 4, 6, 8\}; n_0 = \{5, 10, 15\}$.
- Test $H_{ij} : \mu_{ij} = 0$ versus $H'_{ij} : \mu_{ij} > 0$.
- Set $\mu_{ij} = 3$ for $i = 1, \dots, m - m_0; j = 1, \dots, n - n_0$; the rest of $\mu_{ij} = 0$.
- Selection by generalized Sidak with $k = 1, 2, 3$ and $\alpha_1 = \alpha = 0.05$.

Simulation Results ($k = 1$)

$m = 10, m_0 = 8, n = 20, \mu_1 = 3$

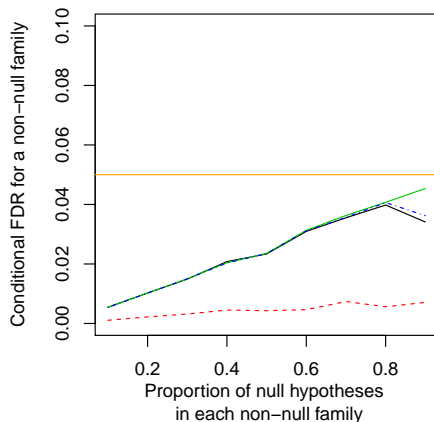
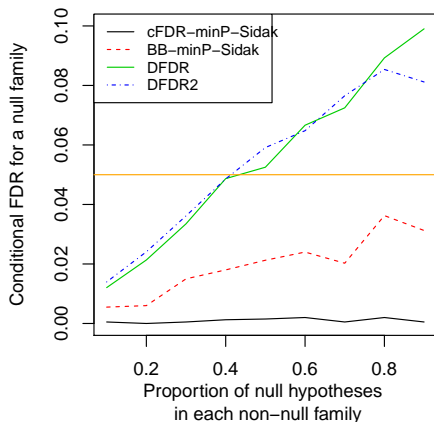


Simulation Results ($k = 1$)



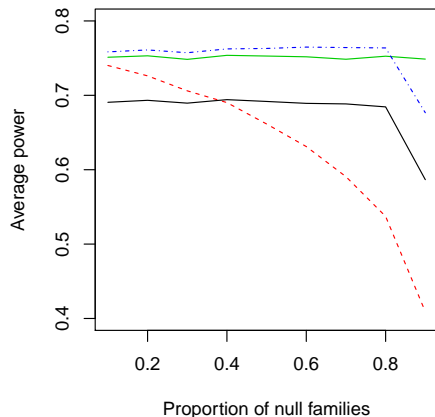
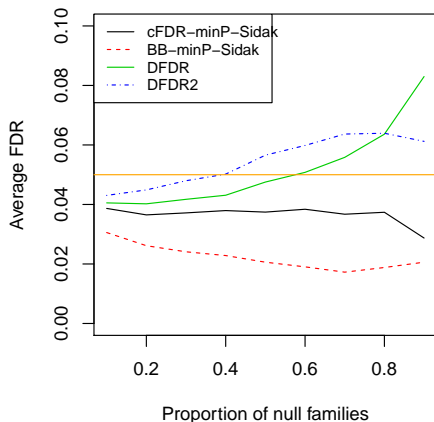
Simulation Results ($k = 1$)

$m = 10, m_0 = 8, n = 20, \mu_1 = 3$



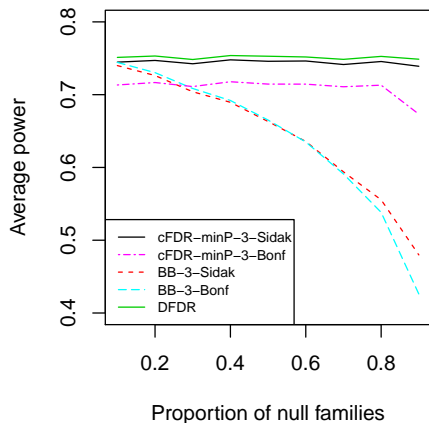
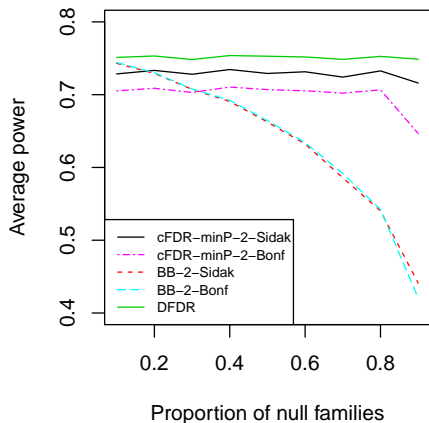
Simulation Results ($k = 1$)

$m = 10, n = 20, n_0 = 15, \mu_1 = 3$



Selection Rule: Bonferroni v.s. Sidak ($k = 2, k = 3$)

$m = 10, n = 20, n_0 = 15, \mu_1 = 3$

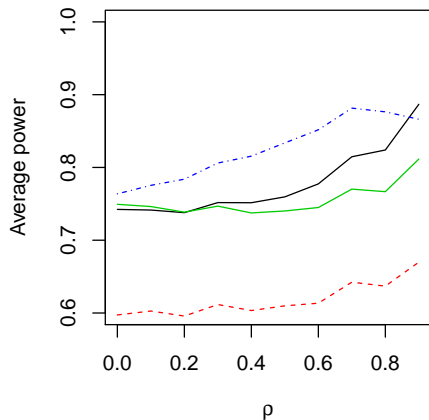
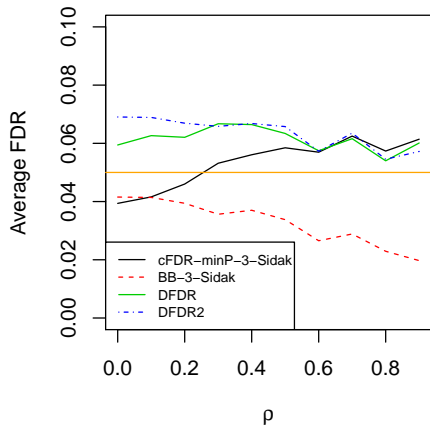


Simulation Settings II: Dependence

- The p -values are **dependent within one body system** with equal correlation and **independent** of the p -values in **other body systems**.
- $m = \{10, 20\}$, $m_0 = 7$, $n = 20$, $n_0 = 15$, $\rho = \{0, 0.1, \dots, 0.9\}$.
- $\alpha_1 = \alpha = 0.05$.
- $B = 2000$ iterations.

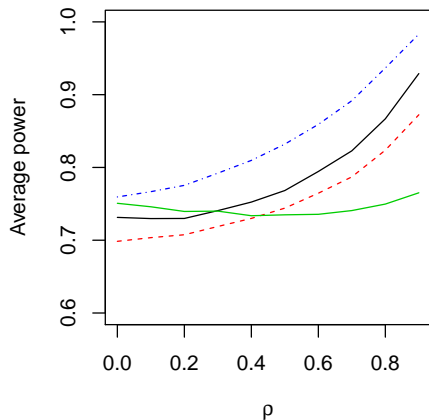
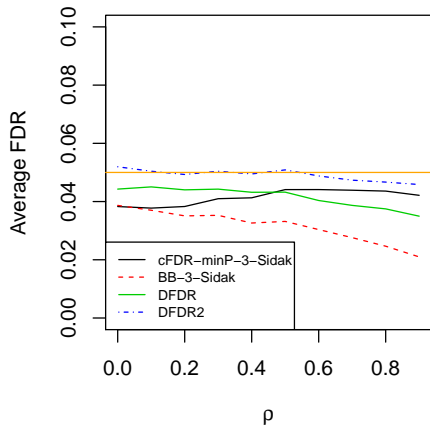
Simulation Results ($m = 10$)

independent families , dependent individuals
 $m = 10$, $m_0 = 7$, $n = 20$, $n_0 = 15$, $\mu_1 = 3$



Simulation Results ($m = 20$)

independent families , dependent individuals
 $m = 20$, $m_0 = 7$, $n = 20$, $n_0 = 15$, $\mu_1 = 3$



Simulation Summary

- The proposed procedure controls **average FDR** along with **k -FWER across families** and **conditional FDR within a family** under all independent and moderate dependent scenarios.
- DFDR and DFDR2 **cannot** control *cFDR for null families* and *average-FDR* under all scenarios! BB procedure **cannot** guarantee *cFDR control for null families* when using k -FWER selection rule with $k > 1$.
- The proposed procedure is more powerful than BB procedure with the same selection rule.

Back to the Motivating Example

Revisit the safety analysis of a candidate vaccine against measles, mumps, rubella and varicella (MMRV)¹.

- Monitor 40 **Tier 2 AE types** from $m = 8$ **body systems**
- $N_1 = 148 \rightarrow \text{MMR} \rightarrow X_{1i}$
 $N_2 = 132 \rightarrow \text{MMRV} \rightarrow X_{2i}$
- Two-sided **Fisher's Exact Test**
- $\alpha_1 = 0.05, \alpha = 0.1$

¹The paper of Mehrotra and Heyse (2004)

A Safety Analysis Example

Table 1: The example from Mehrotra and Heyse (2004) under $\alpha_1 = 0.05$ for selecting BSol and $\alpha = 0.1$ for flagging AEs.

Approach	BSol	Flagging AE
Naive BH	NA	503 (1)
DFDR	5 (1)	503 (1)
DFDR2	5 (1)	503 (1)
GBH	NA	503 (1)
Original BB	5 (1)	503 (1)
cFDR-minP-0.05	2,5,7 (3)	0
cFDR-minP-Sidak-0.05	0	0
cFDR-minP-3-Sidak-0.05	5 (1)	0

Another Safety Analysis Example

Table 2: The Example 4.2 from Mehrotra and Adewale (2012) under $\alpha_1 = 0.05$ for selecting BSol and $\alpha = 0.1$ for flagging AEs. The study monitored 49 AE types across 9 body systems, $N_1 = N_2 = 1616$.

Approach	BSol	Flagging AE
Naive BH	NA	703 (1)
DFDR	3, 7 (2)	301, 704 (2)
DFDR2	7 (1)	703, 704 (2)
GBH	NA	301, 401, 703, 704 (4)
Original BB	7 (1)	703 (1)
cFDR-minP-0.05	1, 2, 3, 4, 6, 7 (6)	301, 703, 704 (3)
cFDR-minP-Sidak-0.05	7 (1)	703, 704 (2)
cFDR-minP-3-Sidak-0.05	3, 7 (2)	703, 704 (2)

Comparisons for Different Approaches

Table 3: Error rates control for different MTPs with multiple families structure

Approach	Family level	Within family	Overall
DFDR	×	×	×
DFDR2	×	×	×
GBH	×	×	global FDR
Original BB	FDR	×	average FDR
cFDR-minP-t (fixed)	×	conditional FDR	average FDR
cFDR-minP-k-Sidak	k-FWER	conditional FDR	average FDR

Discoveries across **body systems selection** (BSol) is considerable important and should be given more attentions for future research!

▸ R package: MHTmult a convenient computing tool to help users make decisions more efficiently.

- Calculating adjusted (conditional) p -values for **multiple families**

MTPs:

```
cFDR.cp.adjust(); DFDR.p.adjust(); DFDR2.p.adjust();  
avgFDR.p.adjust(); GBH.p.adjust()
```

- Calculating adjusted p -values for **k-FWER controlling MTPs:**

```
gbonf.p.adjust(); gsidak.p.adjust()
```

- Options:

- 1 Selection rule (combining method, selecting procedure)
- 2 Decision-making
- 3 Visualization

Summary

- 1 We developed a two-stage multiple testing procedure using minimum p -value to selecting body systems, and efficiently flag the AE types.
- 2 We found out the procedure can guarantee desired type 1 error rate control **across family level, within selected families** and **overall average on selected families**.
- 3 Simulation studies and real data analysis illustrate that the proposed procedures outperform the existing procedures in terms of the error rates control and power. *DFDR procedure cannot control the FDR!*
- 4 Computing tools such as R Package `package: MHTmult` can be easily used, one web application with visualization function is still on work.

Key References

- [1] Benjamini, Y. and Bogomolov, M. (2014) Selective inference on multiple families of hypotheses. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)* 76, 297–318.
- [2] Guo, W. and Romano, J. (2007) A generalized Sidak-Holm procedure and control of generalized error rates under independence. *Statistical Applications in Genetics and Molecular Biology*, 6, 1.
- [3] Heller, R., Chatterjee, N., Krieger, A., and Shi, J. (2016) Post-selection inference following aggregate level hypothesis testing in large scale genomic data. *bioRxiv*, 058404.
- [4] Mehrotra, D. V. and Adewale, A. J. (2012) Flagging clinical adverse experiences: reducing false discoveries without materially compromising power for detecting true signals. *Statistics in Medicine*, 31, 1918–1930.
- [5] Mehrotra, D. V. and Heyse, J. F. (2004). Use of the false discovery rate for evaluating clinical safety data. *Statistical Methods in Medical Research*, 13, 227-238.

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