

Gene Mutations Associated with HIV-1 Drug Resistance

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1.0.0 BackGround

- Understanding the genotype-phenotype correlation guiding clinic treatment.
- Rhee et al. (2006) related HIV-1 protease and reverse transcriptase mutations to in vitro susceptibility to 16 antiretroviral drugs.

1.0.1 Our Target

- Detect gene mutations associated with HIV-1 drug resistance.

1.0.2 Challenges

- Sample size v.s. the complete gene mutations;
 - Shrink the candidate set via expert information;
 - Obtaining data is expensive.
- Reliable simultaneous inference on various genes.
 - Not just variable selection!

1.1.1 Source of HIV Data Set

- We use HIV Data Set described and analyzed by Rhee et al. (2006);
- The ground truth is provided by Rhee et al. (2005);
- Additional information is available at PI, NRTI, NNRTI and THE WORLD HEALTH ORGANIZATION 2009 LIST OF MUTATIONS.

1.1.2 HIV-1 Drugs

Drug Class ¹	PI:	APV	ATV	IDV	LPV	NFV	RTV	SQV
	NRTI:	X3TC	ABC	AZT	D4T	DDI	TDF	
	NNRTI:					DLV	EFV	NVP

1.1.3 Genotype

- Position: $P1 \sim P99$ in PI and $P1 \sim P240$ in NRTI and NNRTI;
- Mutative Direction: On each position, there are several possible mutation directions, A, B, \dots

¹To avoid ambiguity, we use drug class to denote macro-categories (PI, NRTI, NNRTI) and use drug type to denote the micro-categories (APV, ATV, IDV, LPV, ...)

1.2.1 Two Detection Cases

- Why?
 - The targets of genotype detection (1.1.3) vary;
- What?
 - **Case I:** Detect the mutative positions, e.g. P_1, P_2, \dots .
 - **Case II:** Detect the mutative positions and the mutative directions simultaneously, e.g. $P1.A, P1.B, \dots$.
- How? (Multiple Testing)
 - 1 Determine detection case (e.g. Case I w.r.t APV);
 - 2 Obtain Hypotheses $\{H_i\}_{i \in \{P_1, P_2, \dots, P_{99}\}}$
 - $H_{P_1} = 1 \Rightarrow$ the gene mutation on position P_1 associated with HIV-1 drug resistance.
 - 3 Run selection procedure to test H_i simultaneously.

1.2.2 Discovery Table: Applying a selection procedure, we get Table 1

Table: Discovering Table of m hypothesis

Hypothesis	\mathcal{H}_0	\mathcal{H}_1	
Reject	V	S	R
Fail to Reject	U	T	W
Total	m_0	m_1	m

1.2.3 Criteria for Selection

- False Discovery Proportion: $FDP = \frac{V}{R \vee 1}$.
- Discovery Proportion: $DP = \frac{S}{m_1}$.
- **Groupwise FDP:**
 - When the gene can be separated into groups A_1, A_2, \dots, A_G ;
 - $H_{A_i} = 0 \Leftrightarrow \exists k \in A_i$ s.t. $H_k = 0$;
 - Implement multiple testing on $\{H_{A_i}\}_{i=1,2,\dots,G}$

Introduction

Multilayer Hypothesis Testing

1.3.1 Intuition and Idea

- Can we consider Case I and Case II together?
- Conduct multiple testing with several group information;

1.3.2 Possible Group Information

- The drug types within the same class;
- The genes within the same position.

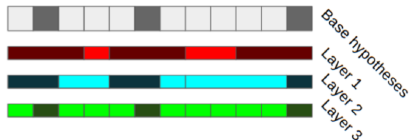


Figure: Multiple Group Information induces Multilayer Hypothesis Testing Problem

2.1.1 Multi-Task Model

Inspired by Dai and Barber (2016), we considered a multi-task problem.

Upon fixing a drug class, like *PI*, the model becomes

$$\mathbf{Y} = \mathbf{XB} + \mathbf{E}.$$

where

- $\mathbf{Y} \in \mathbb{R}^{n \times r}$, $\mathbf{X} \in \mathbb{R}^{n \times p}$, $\mathbf{B} \in \mathbb{R}^{p \times r}$ and $\mathbf{E} \in \mathbb{R}^{n \times r}$;
- Y_{ij} : the response of isolates i with one drug type j ;
- X_{ij} : the indicator of isolates i corresponding to gene mutative direction $j \in \{P1.A, P1.B, \dots\}$;
- B_{ij} : the underlying effect of drug resistance associated with gene i with respect to HIV drug type j ;
- Since the mechanisms of different drug types within a drug class are similar, we can assume B is **row-sparsed**.

2.1.2 Single-Task Model with Group Info

Denote $y = \text{vec}(\mathbf{Y})$, $\epsilon = \text{vec}(\mathbf{E})$, $\beta = \text{vec}(\mathbf{B})$, $\mathbb{X} = \mathbf{I}_r \otimes \mathbf{X}$, the model becomes²

$$y = \mathbb{X}\beta + \epsilon.$$

Then, the group information is available and FDP is defined groupwise.

- **Layer I:**
 - By gene mutative position;
 - Group partition: $\{A_{P1}, A_{P2}, \dots, A_{P99}\}$.
- **Layer II:**
 - By gene mutative position and direction;
 - Group partition: $\{A_{P1.A}, A_{P1.B}, \dots, A_{P99.d}\}$.

²We remove the gene mutative direction whose frequencies is less than 3 and the possible duplicates.

2.1 Possible Algorithms:

- BH Procedure (Benjamini and Hochberg (1995));
- P-filter (Barber and Ramdas (2017));
- Knockoff (Barber and Candès (2015));
- Multilayer Knockoff (Katsevich and Sabatti (2019)).

Among these method,

- Multilayer Knockoff and p-filter could simultaneously control false discovery rate in different layers;
- p-value based procedure performs stablier than Knockoff method does.

Thus, we prefer **p-filter**.

2.2.1 What does p-filter do?

- Control the groupwise FDR at α_k within the Layer k .

2.2.2 How to reject? (e.g. Two Layers)

- Given two dimension threshold (t_1, t_2) , the rejection set is

$$R(t_1, t_2) = \left\{ i : p_{g_1(i)1} > t_1, p_{g_2(i)2} > t_2, i \in A_{g_m(i)}^m \right\}.$$

2.2.3 How to control? (At Layer k)

- Construct p values for group g through Simes Test p_g^{Simes} ;
- Then expected false rejection is approximately bounded by $\sum_{g \in \mathcal{H}_0^k} \mathbf{1}\{p_g^{Simes} \leq t_k\} \preceq G_k \times t_k$;
- The upper estimator of FDP is $\widehat{FDP}_k = \frac{G_k \times t_k}{R(t_1, t_2) \vee 1}, m = 1, 2, \dots$.

Result and Discussion

FDP and DP

We conducted these algorithms with p filter code, multilayer knockoff code and Knockoff Guide.

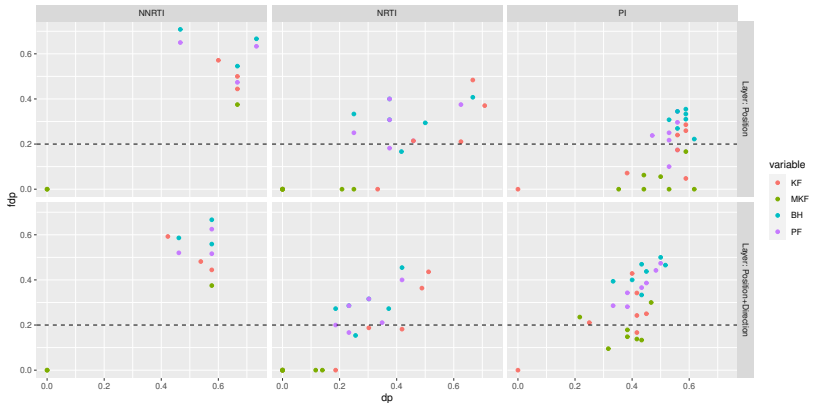


Figure: The FDP and DP for different drug types of the drug class PI, NRTI and NNRTI. KF is knockoff filter (Case I), MKF is multilayer knockoff filter (Case I and Case II), BH is Benjamini Hochberg procedure (Case I) and PF is p-filter (Case I and Case II)

Result and Discussion

FDP and DP

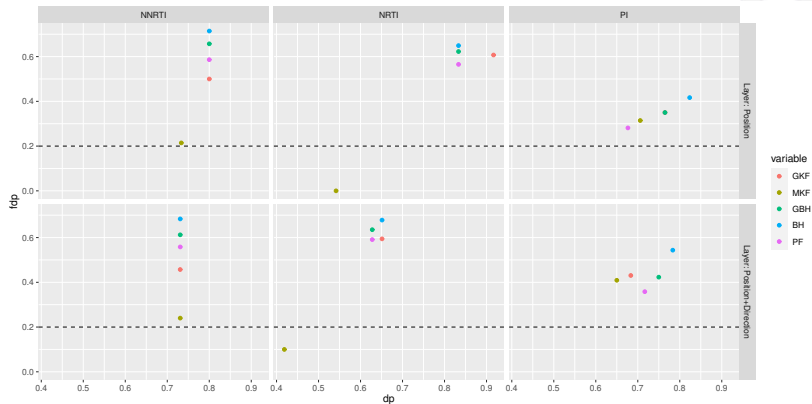


Figure: The FDP and DP for three drug classes PI, NRTI and NNRTI. GKF is group knockoff filter (Layer I), MKF is multilayer knockoff filter (Layer I and Layer II), BH is Benjamini Hochberg procedure (Case I), BH is groupwise Benjamini Hochberg procedure (Layer I) and PF is p-filter(Layer I and Layer II).

Result and Discussion

Mutative Frequencies

We also investigated whether low mutative frequencies leads to low accuracy in Case II. The selection procedure used in this section is p-filter.

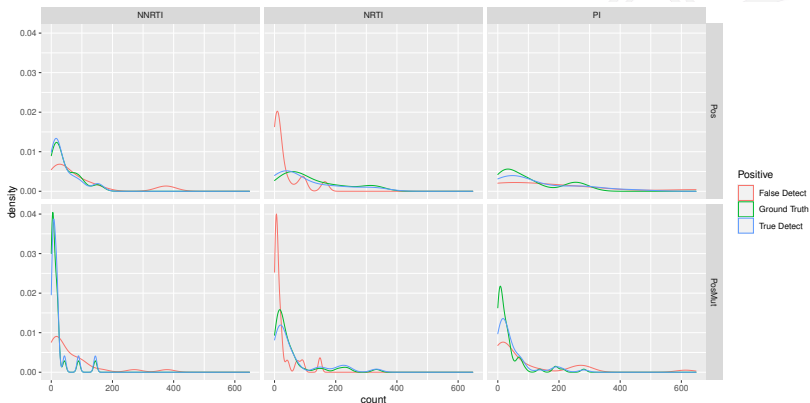


Figure: The empirical density of the position + mutative direction count for three drug classe.

Result and Discussion

New Discovered Genes

Additional information is provided in PI, NRTI and NNRTI and THE WORLD HEALTH ORGANIZATION 2009 LIST OF MUTATIONS.

Table: New Discovered HIV-1 Drug Resistance related Gene Mutation

Drug Class	Neg Gene	Neg Gene Position
PI	P10.I P10.L P10.V P20.R P36.I P36.L P37.S P63.H P63.P P64.I P64.V P67.Y P71.T P71.V P82.I P91.S P93.L	36 37 63 64 91 93
NRTI	P103.N P118.V P121.H P135.T P142.V P162.Y P180.V P181.C P181.V P203.D P215.D P227.L P35.I P35.R P40.F P4.S P70.G P83.K	103 118 121 135 142 162 180 181 227 35 40 4 83
NNRTI	P101.H P101.Q P135.T P138.A P139.R P179.D P179.E P184.V P215.Y P219.N P49.R P74.V P98.G	135 139 179 184 215 219 49 74 98

Guidance for Future Clinic Experiments:

- We report some valuable gene mutations for three drug classes respectively;
- The new discovered genes is worth considering in future clinic experiments;
- In the past, fewer experiments is conducted on NRTI and NNRTI, so the supporting information is less.
- However, the success in PI highly sustains more experiments on NRTI and NNRTI.

Thank You!



More Informations could be found on

- Github Address: Github
- Visualization: Shiny
- Report: Report



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