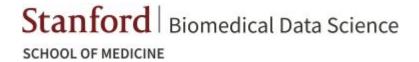
# Selecting Genetic Variants Using Knockoff Under Collider Bias

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Symptoms & Diagnosis







What are common and distinct pathways of severe mental illnesses?



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Symptoms & Diagnosis

Neurocognitive function







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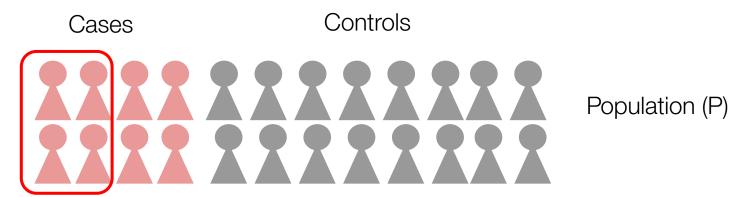
- Demographics
- Medication
- Substance use
- ..

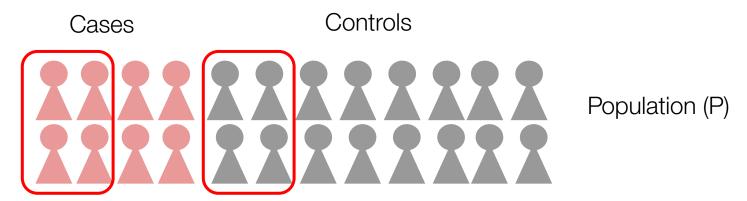
What are common and distinct pathways of severe mental illnesses?

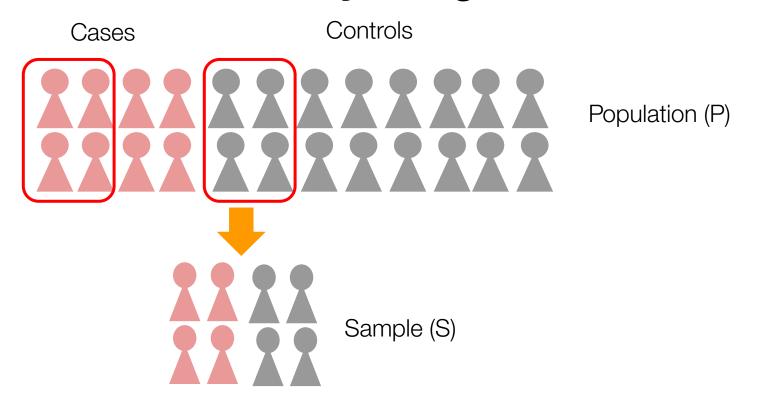


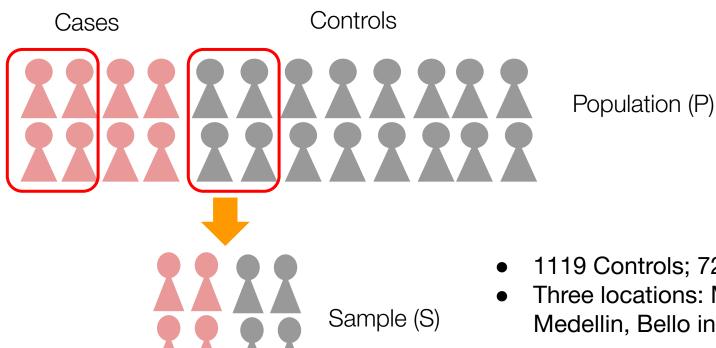
Cases Controls

Population (P)









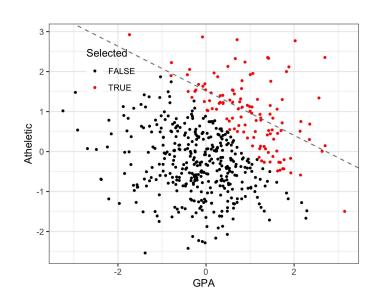
- 1119 Controls; 7246 Cases
- Three locations: Manizales, Medellin, Bello in Columbia

# Example: Is academic ability associated with athletic ability?

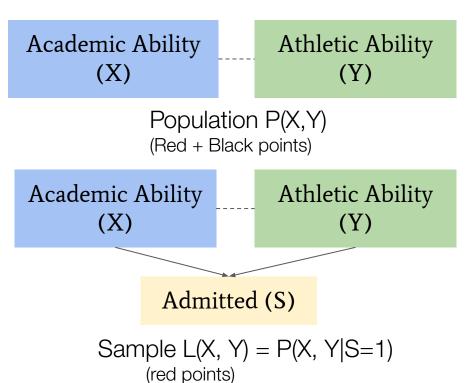
Academic Ability (X)

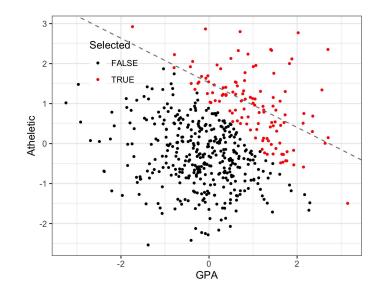
Athletic Ability (Y)

Population P(X,Y) (Red + Black points)

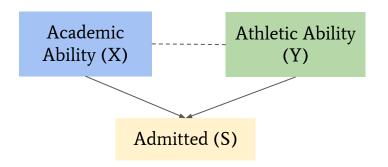


# Example: Is academic ability associated with athletic ability?

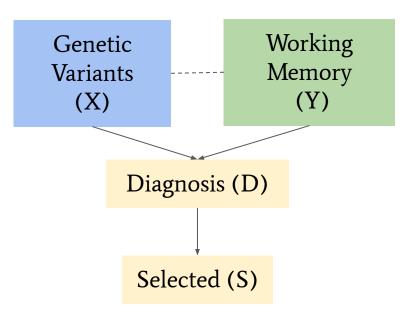




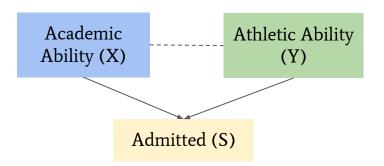
#### **Collider Bias**



#### Case-control study

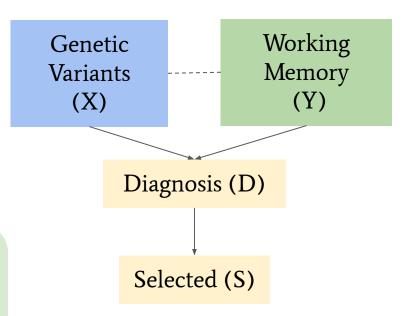


#### **Collider Bias**

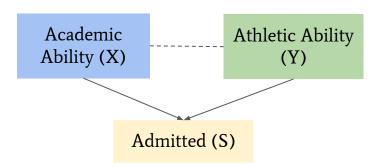


Can we test if X affects Y in the population (P) using case case-control sample (S)?

#### Case-control study

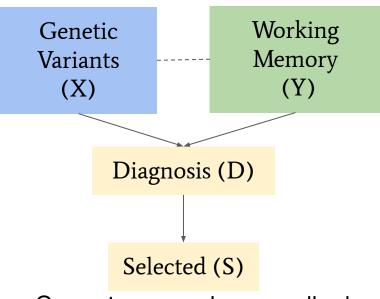


#### **Collider Bias**



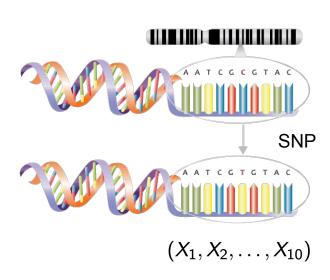
Can we test if X affects Y in the population (P) using case case-control sample (S)?

#### Case-control study



Current approaches usually do not apply when the number of variables is large!

# A knockoff approach to select variables in the high-dimensional setting



- Single nucleotide polymorphisms (SNP) are alterations in a single nucleotide (A, T, G, C) in the DNA sequence.
- Denote the SNPs as

$$(X_1, X_2, \ldots, X_p)$$

- Denote the endophenotype as Y.
- Identify important SNPs by testing

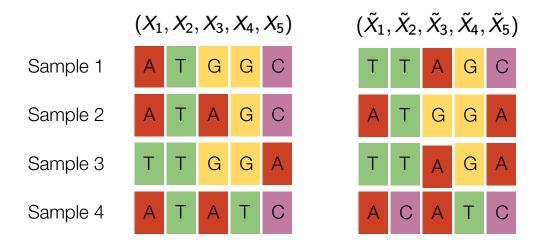
$$\mathcal{H}_j: X_j \perp \!\!\!\perp Y \mid X_{-j}$$

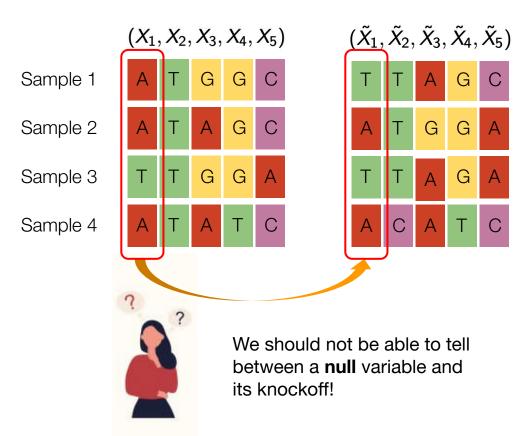
 The knockoff method is a variable selection procedure that controls the false discovery rate

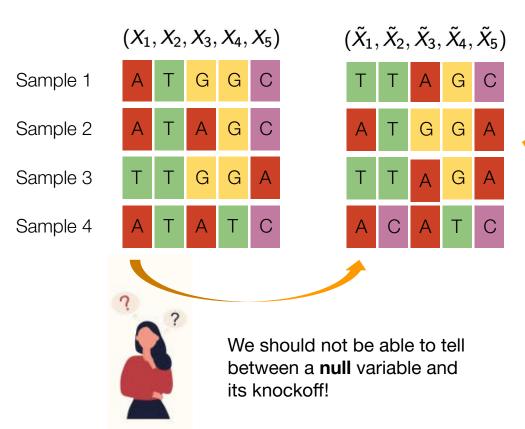
- The knockoff method is a variable selection procedure that controls the false discovery rate
- For every observation  $(X_1, X_2, ..., X_p)$ We construct **knockoff variables**  $(\tilde{X}_1, ..., \tilde{X}_p)$ Such that

$$(X_1,\ldots,X_p,\tilde{X}_1,\ldots,\tilde{X}_p)_{\text{Swap S}}\stackrel{d}{=}(X_1,\ldots,X_p,\tilde{X}_1,\ldots,\tilde{X}_p)$$

For every set S containing only **null** variables



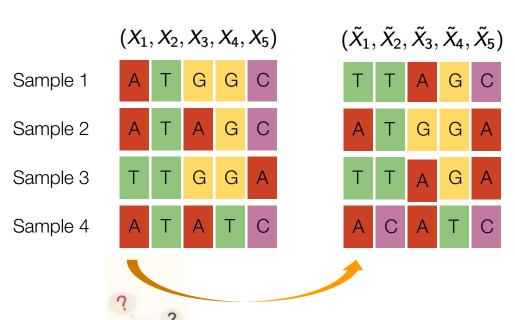




#### Feature importance statistics

$$(Z_1,Z_2,\ldots,Z_5,\tilde{Z}_1,\tilde{Z}_2,\ldots,\tilde{Z}_5)$$





its knockoff!

We should not be able to tell between a **null** variable and

Feature importance statistics

$$(Z_1,Z_2,\ldots,Z_5,\tilde{Z}_1,\tilde{Z}_2,\ldots,\tilde{Z}_5)$$

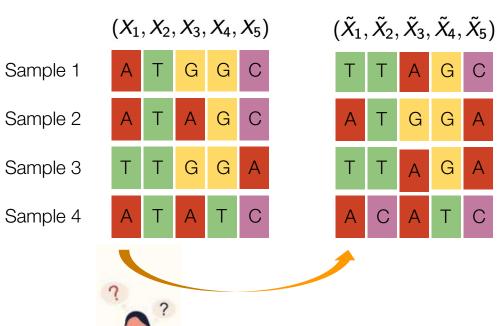
E.g. LASSO regression coefficients



**Scores** 

 $(W_1, W_2, W_3, W_4, W_5)$ 

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



We should not be able to tell between a variable and its knockoff!

#### Feature importance statistics

$$(Z_1,Z_2,\ldots,Z_5,\tilde{Z}_1,\tilde{Z}_2,\ldots,\tilde{Z}_5)$$

E.g. LASSO regression coefficients



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A list of selected variables

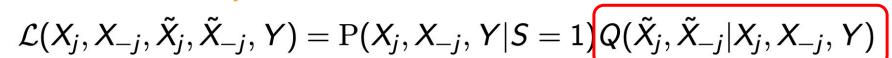
$$(X_j, X_{-j}, \tilde{X}_j, \tilde{X}_{-j}, Y) \stackrel{d}{=} (\tilde{X}_j, X_{-j}, X_j, \tilde{X}_{-j}, Y)$$

$$(X_j, X_{-j}, \tilde{X}_j, \tilde{X}_{-j}, Y) \stackrel{d}{=} (\tilde{X}_j, X_{-j}, X_j, \tilde{X}_{-j}, Y)$$



$$\mathcal{L}(X_j, X_{-j}, \tilde{X}_j, \tilde{X}_{-j}, Y) = P(X_j, X_{-j}, Y | S = 1) Q(\tilde{X}_j, \tilde{X}_{-j} | X_j, X_{-j}, Y)$$

$$(X_j, X_{-j}, \tilde{X}_j, \tilde{X}_{-j}, Y) \stackrel{d}{=} (\tilde{X}_j, X_{-j}, X_j, \tilde{X}_{-j}, Y)$$





User defined!

$$(X_j, X_{-j}, \tilde{X}_j, \tilde{X}_{-j}, Y) \stackrel{d}{=} (\tilde{X}_j, X_{-j}, X_j, \tilde{X}_{-j}, Y)$$

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We don't know what is P(X, Y)!

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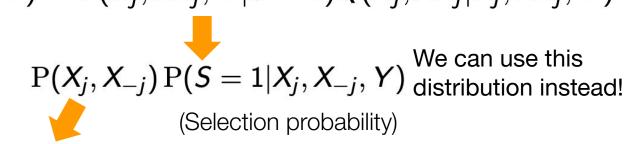
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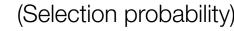
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$$P(X_{j}, X_{-j}) P(S = 1 | X_{j}, X_{-j}, Y)$$
We can use this distribution instead! (Selection probability)

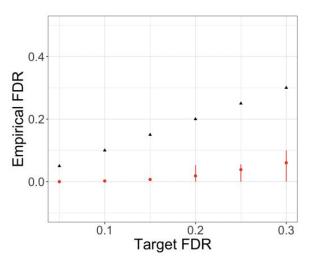
$$(X_j, X_{-j}, \tilde{X}_j, \tilde{X}_{-j}, Y) \stackrel{d}{=} (\tilde{X}_j, X_{-j}, X_j, \tilde{X}_{-j}, Y)$$

$$\mathcal{L}(X_j,X_{-j},\tilde{X}_j,\tilde{X}_{-j},Y) = \mathrm{P}(X_j,X_{-j},Y|\mathcal{S}=1)Q(\tilde{X}_j,\tilde{X}_{-j}|X_j,X_{-j},Y)$$





$$\propto P(X_i|X_{-i},Y,S=1)$$



lf

$$P(X_j, X_{-j}) P(S = 1 | X_j, X_{-j}, Y)$$

Is multivariate Gaussian, then we can sample knockoffs from another multivariate Gaussian.

Number of cases = Number of controls = 1,000; Number of variables = 200; X is from a multivariate Gaussian distribution where the covariance matrix is block diagonal (block size = 10); Y is from a linear model where 10% of the variables are non-nulls;

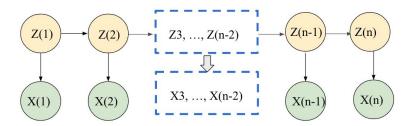
$$P(D = 1|X, Y) = e^{-v^2/2}, v = \gamma_0 Y + X^{\top} \gamma.$$

#### Conclusion and remaining challenges

- Collider bias can occur in many studies!
- We describe one way to adjust the knockoff sampling procedure to select variables that controls the false discovery rate (1) in high-dimensions (2) under collider bias

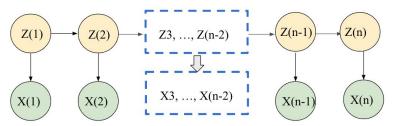
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- It's unclear how to define  $Q(\tilde{X}_j, \tilde{X}_{-j}|X_j, X_{-j}, Y)$
- One idea: approximate  $P(X_j, X_{-j}) P(S = 1 | X_j, X_{-j}, Y)$  by another distribution for which we know Q



# Thank you! Questions?