## GENE-ENVIRONMENT INTERACTION IN THE ERA OF PRECISION MEDICINE

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## THE CURRENT PARADIGM

$$P = G + E$$

## Assumptions:

- genetic (G) and environmental (E) factors independently contribute toward a given phenotypic trait (P)
- G is the aggregated contribution from multiple independent individual loci
- E is any variance in P not explained by G

**Definition:** (narrow-sense) heritability is the fraction of phenotypic variance explained by genetic variance.



## PROBLEM: MISSING HERITABILITY

For many diseases with a strong genetic underpinning, the classical association framework usually cannot identify significant signals.

#### CLAIM

Missing heritability results from model insufficiency. Linear models cannot capture the intrinsic complexity of complex diseases involving hundreds or thousands of at-risk loci.

## PROBLEM: INDIVIDUAL DIVERSITY

Epidemiological studies estimate risk at a population level, which may not be applicable to personalized health management since individuals have vast differences in lifestyles, behaviors, physiologies, exposomes, and genetic predispositions.

#### CLAIM

Technological advancement is needed to acquire and assemble non-genetic data at a personal resolution.

## MISSING HERITABILITY

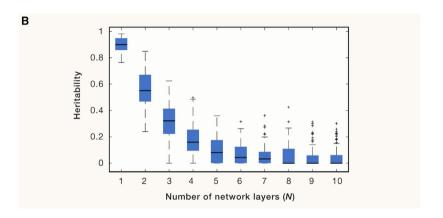
## A SIMULATION STUDY

Α

10,000 sites 1,000 individuals Site 1: 0/1 Site 2: 1/1 Site 3: 1/1 Output layer Site 4: 0/1 Intermediate layers N=1 N=2 N=3N = 10linear non-linear

Personal genomes

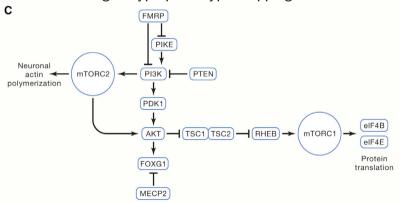
## SIMULATION RESULTS



Note: heritability estimated using GCTA (genome-wide complex trait analysis) package.

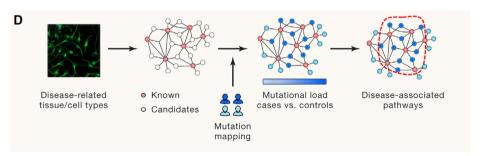
## EXAMPLE: PI3K/AKT/MTOR PATHWAY

Duplicate genes and epistatic interactions between genes yield nonlinear genotype-phenotype mappings.



## POTENTIAL SOLUTIONS

- Re-construct a reference cellular map using multiomic approaches
- Select the minimal subset of genes whose mutation patterns distinguish cases from controls using sparse learning



## Individual Diversity

## MEASURING ENVIRONMENTAL FACTORS

## Limitations of epidemiological studies:

- Population-level estimates might not apply to a specific individual
- Data from participant surveys or clinical records is sparse and collected at (relatively few) discrete time points

## Benefits of wearable technology:

- Widely available (e.g. smart watches and fitness trackers)
- Continuously track individual-level physiological and environmental parameters in real time
- More accurate than surveys, e.g. galvanic skin response devices instead of survey questions on stress levels



## BAYESIAN VIEW OF HERITABILITY

# BADGE (BAYESIAN AGGREGATION OF DISEASE GENOMICS AND ENVIRONMENT)

Assumption: disease outcome (D), genetic risk (G), and environment contributors (E) can be modeled by a joint probability Pr(D, G, E).

Then (population level) disease prevalence is

$$Pr(D) = \int Pr(D \mid G, E) Pr(G, E) dGdE$$
 (1)

(Population level) environmental contribution to disease outcome is

$$Pr(D \mid E) = \int Pr(D \mid G, E) Pr(G) dG$$
 (2)

## BADGE (CONTINUED)

(Personal) genomic contribution to disease outcome is

$$Pr(D \mid G) = \int Pr(D \mid G, E) P(E) dE$$
(3)

Personal genome given personal clinical outcome is

$$Pr(G \mid D) = \frac{Pr(D \mid G)Pr(G)}{\int Pr(D \mid G)Pr(G)dG}$$
(4)

## Genetic Coefficient

**Definition:** genetic coefficient of a disease:

$$C = JS(Pr(G \mid D = 1) \parallel Pr(G \mid D = 0))$$
 (5)

where JS is the Jensen-Shannon divergence between two distributions.

Intuitively, C represents the distinguishability of case genomes (D=1) from control genomes (D=0).

