

Population-specific causal disease effect sizes in functionally important regions impacted by selection

ASHG 2019

October 17, 2019

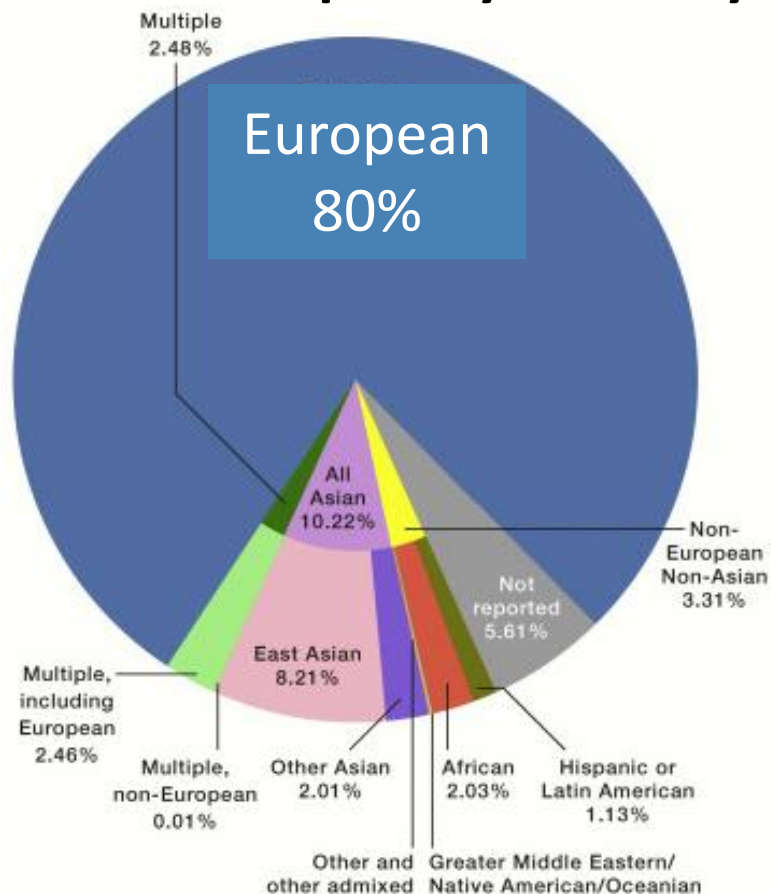
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Alkes Price Group

Harvard University & Broad Institute

Most GWAS samples are still European

GWAS samples by ethnicity



non-European 20%

(Sirugo, Williams, Tishkoff 2019 *Cell*)

GWAS is becoming more diverse

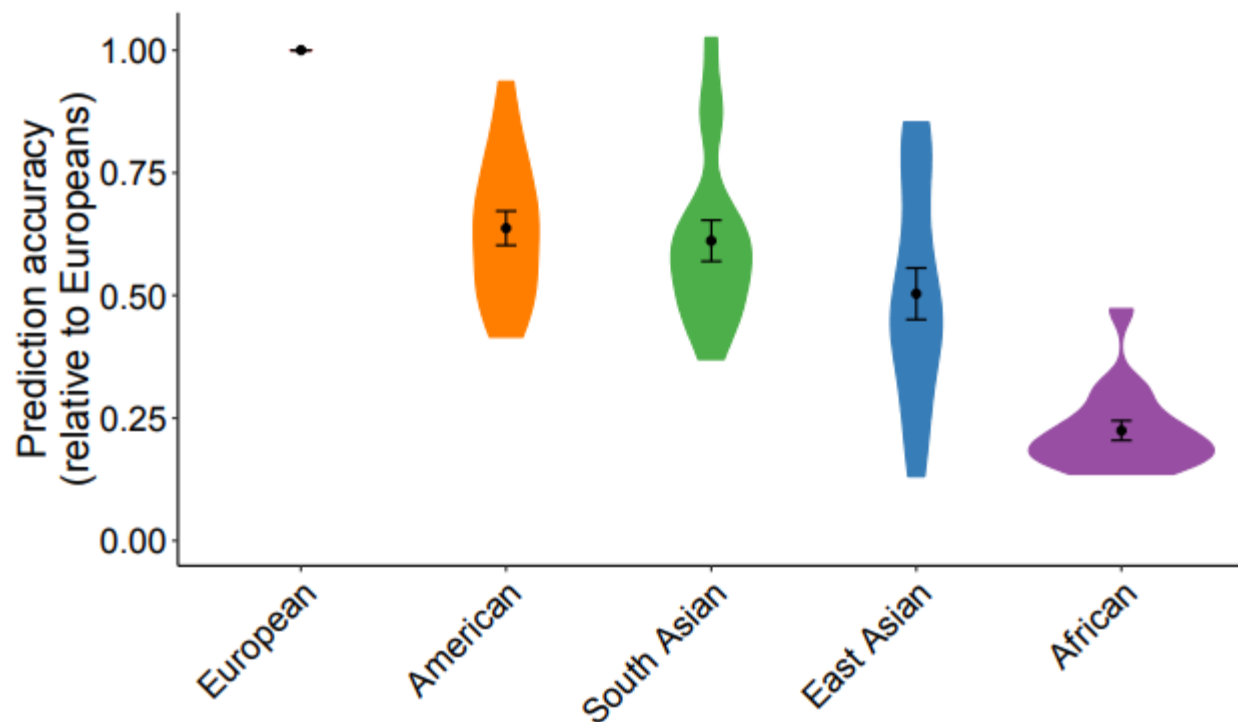
Number of non-European GWAS samples

- 2009: 0.1 million
 - 2016: 7.0 million
- } **70x**

(Popejoy & Fullerton 2016 *Nature*)

Trans-ethnic genetic risk prediction has limited accuracy

Relative to Europeans, trans-ethnic genetic risk prediction is less accurate for non-Europeans



(Martin et al. 2019 *Nat Genet*)

Factors impacting prediction accuracy

- Different LD patterns
- Population-specific variants

.....

(Marquez-Luna et al. 2017 *Genet Epidemiol*)

- **Different causal effect sizes?**

Trans-ethnic genetic correlations are less than 1

- **Schizophrenia:** **0.6** (AFR American – EUR)
(de Candia et al. 2013 *AJHG*)

- **Prostate cancer:** **0.9** (EAS – EUR)
0.6 (AFR American – EUR)
(Mancuso et al. 2016 *Nat Genet*)

- **Rheumatoid arthritis:** **0.5** (EAS – EUR)
(Brown et al. 2016 *AJHG*;
Galinsky et al. 2019 *Genet Epidemiol*)

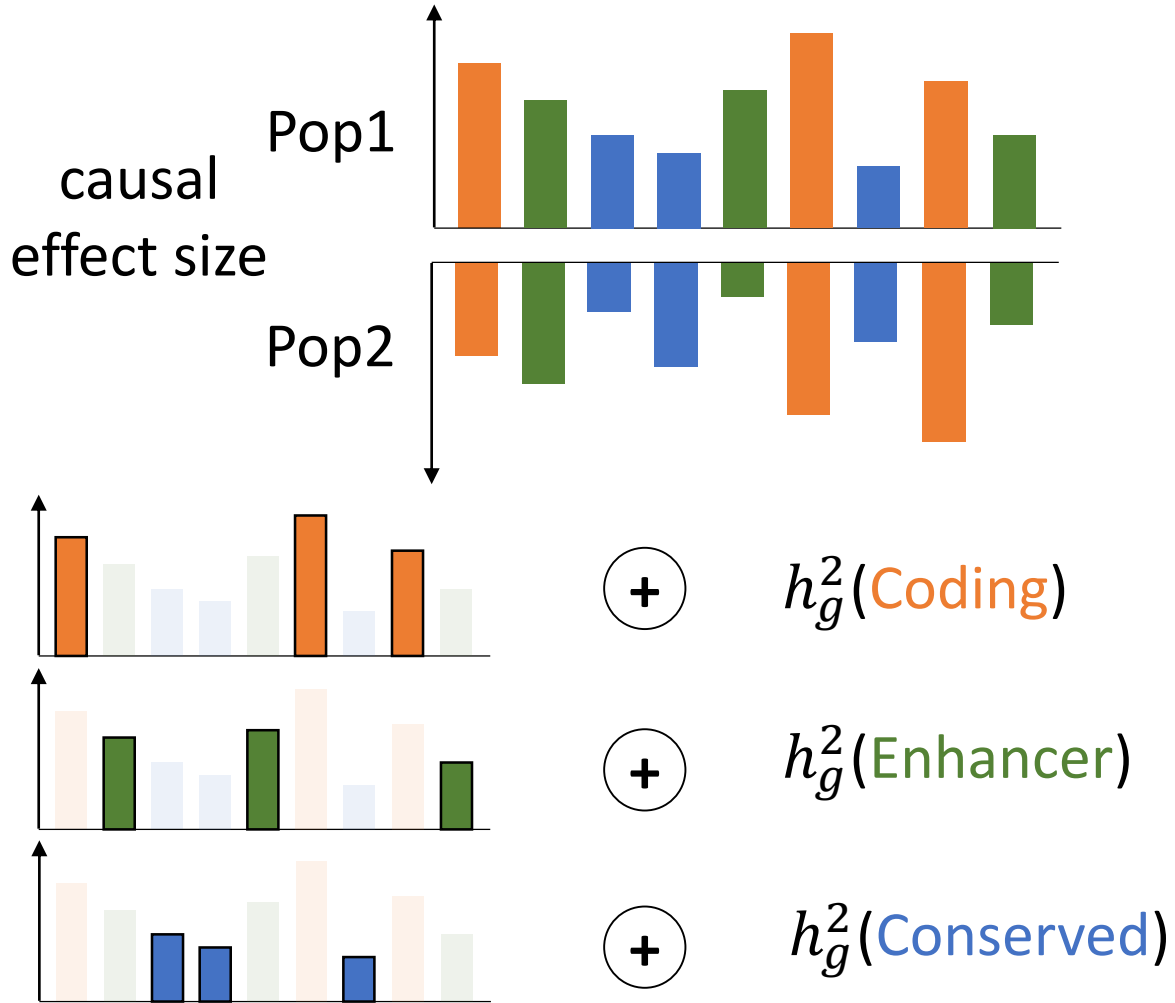
- **Average across 22 traits:** **0.8** (EAS – EUR)
(Martin et al. 2019 *Nat Genet*)

Why is trans-ethnic genetic correlation imperfect?

Stratifying trans-ethnic genetic correlation

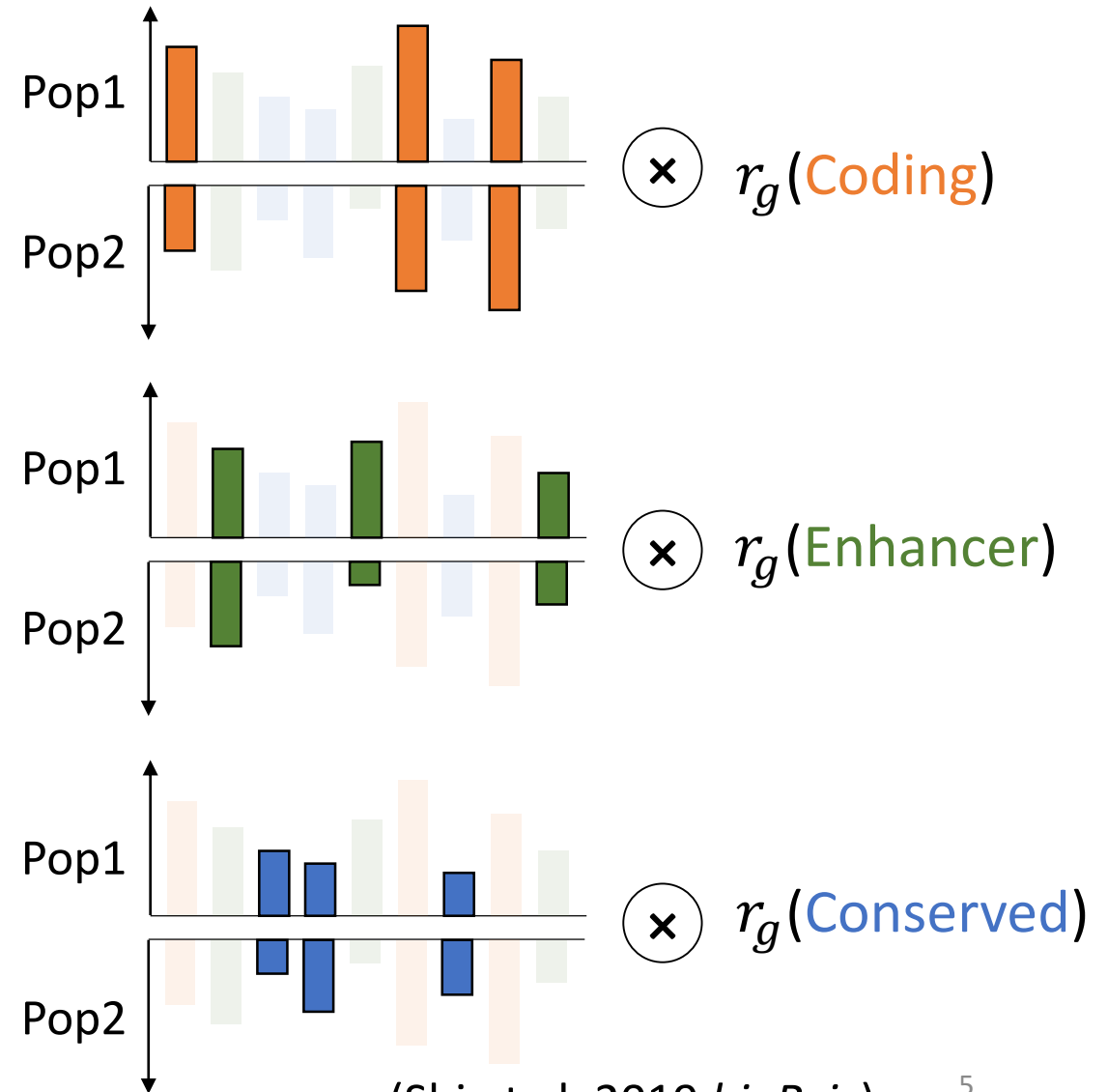
Stratifying heritability

■ Coding
 ■ Conserved
 ■ Enhancer



(Finucane et al. 2015 *Nat Genet*)

Stratifying trans-ethnic genetic correlation (r_g)



(Shi et al. 2019 *bioRxiv*)

Outline

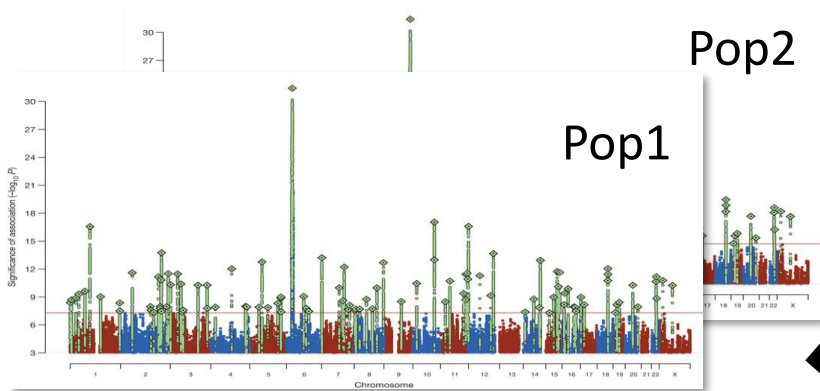
- Method to stratify trans-ethnic genetic correlation (S-LDXR)
- Analysis of 30 complex diseases and traits
- Interpretation: potential role of positive selection

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- Method to stratify trans-ethnic genetic correlation (S-LDXR)
- Analysis of 30 complex diseases and traits
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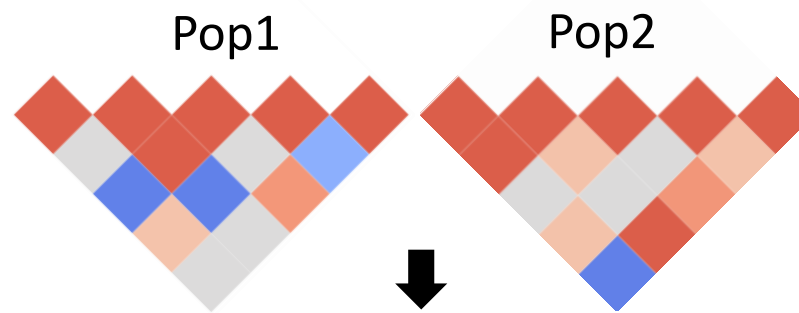
S-LDXR stratifies *squared* trans-ethnic genetic correlation from GWAS summary statistics

GWAS summary statistics
(in 2 populations)

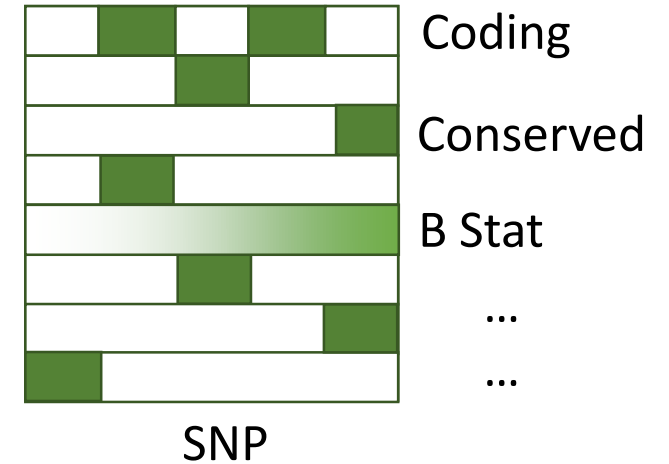


PGC 2014 *Nature*

reference LD (1000 GP)
(in 2 populations)



Genomic annotations
(binary and continuous)



S-LDXR with baseline-LD-X model
(62 genomic annotations)

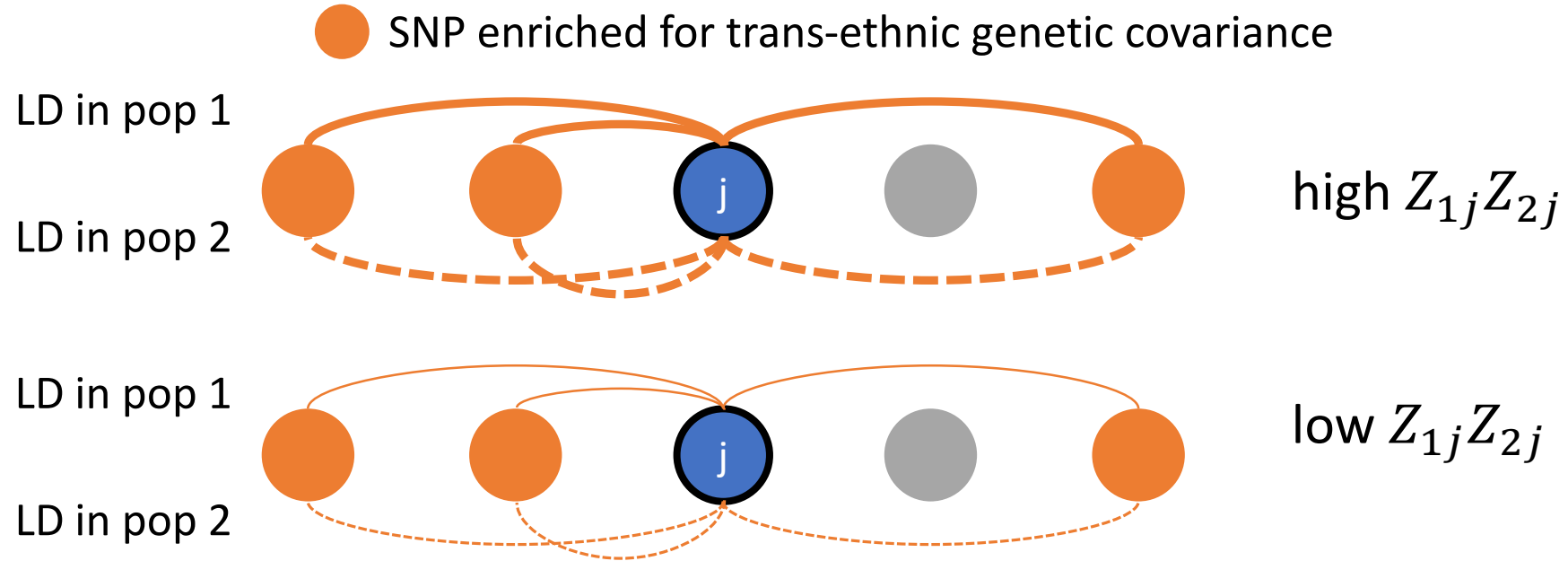
S-LDXR models per-allele effect sizes, accounting for MAF differences, different from S-LDSC

enrichment of trans-ethnic r_g^2 in annotation C

$$\lambda^2(C) = \frac{r_g^2(C)}{r_g^2}$$

use shrinkage to reduce noise

Product of Z-scores is higher for SNPs tagging annotations enriched for trans-ethnic genetic covariance



$$E[Z_{1j}Z_{2j}] = \sqrt{N_1 N_2} \sum_C l_{\times j}(C) \theta_C$$

GWAS sample sizes

Z-score of SNP j in population 1 and 2

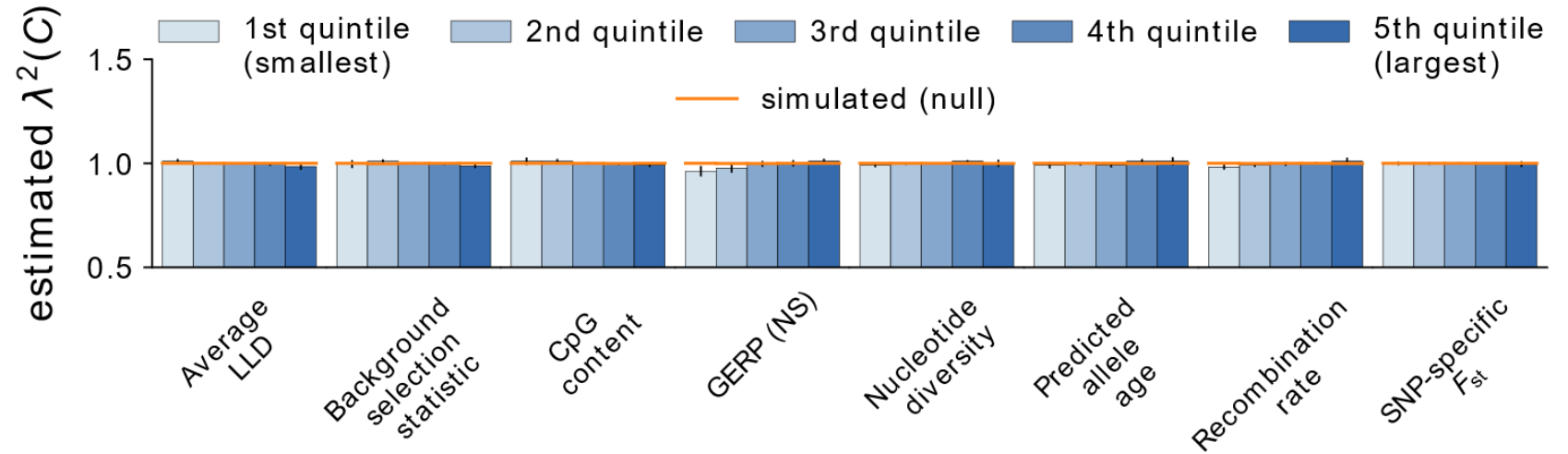
trans-ethnic LD score

net contribution of annotation C

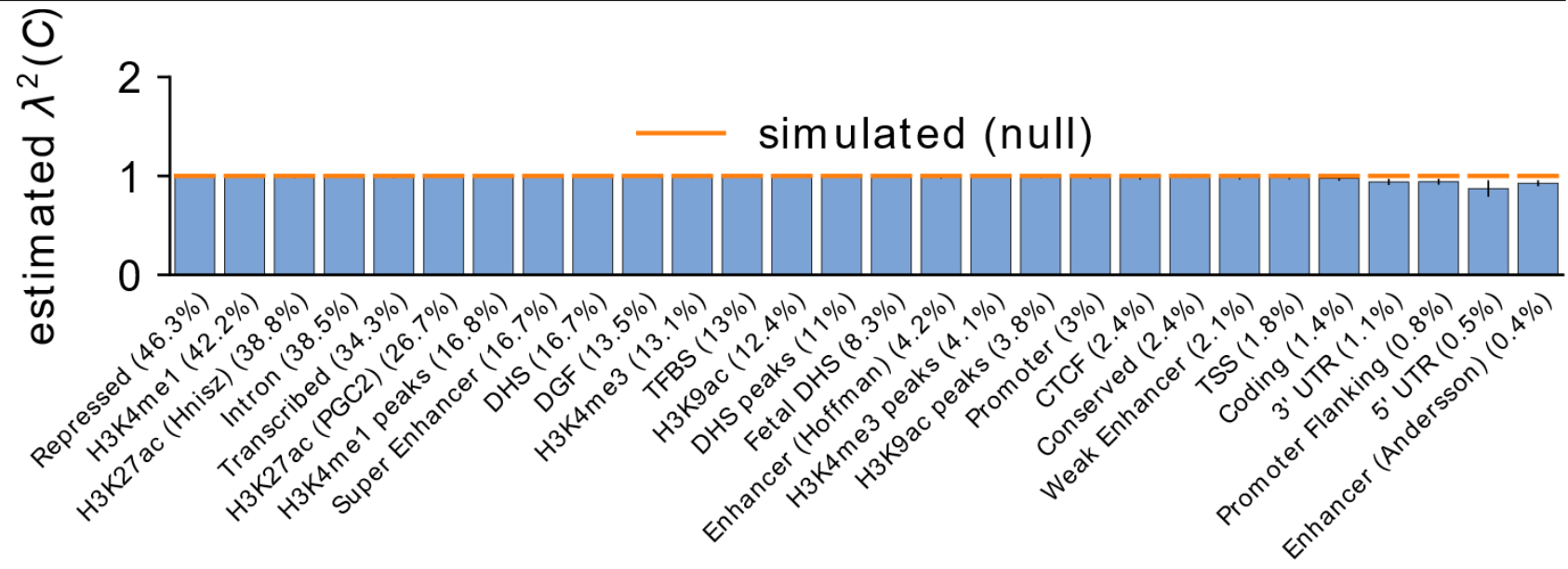
S-LDXR is unbiased in null simulations

simulated $\lambda^2(C) = 1$ for all annotations

$\lambda^2(C)$: enrichment of squared trans-ethnic genetic correlation in annotation C



- Quintiles of continuous-valued annotations (Gazal et al. 2017 *Nat Genet*)



- 28 binary functional annotations (Finucane et al. 2015 *Nat Genet*)

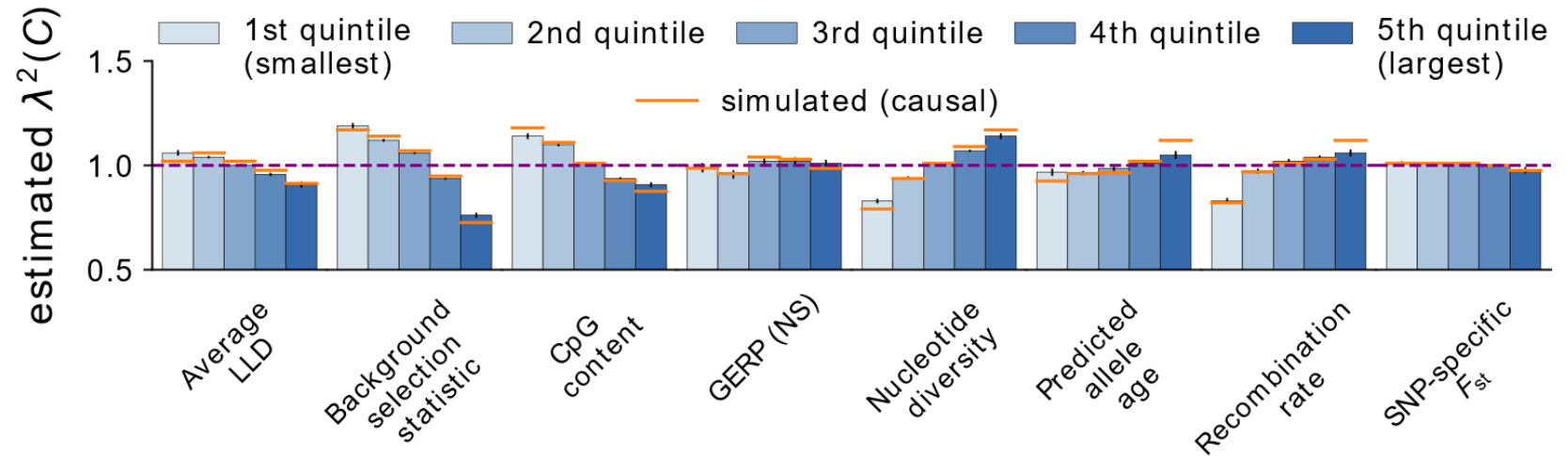
S-LDXR is conservative in causal simulations

simulated $\lambda^2(C)$ informed by real traits

$\lambda^2(C)$: enrichment of squared trans-ethnic genetic correlation in annotation C

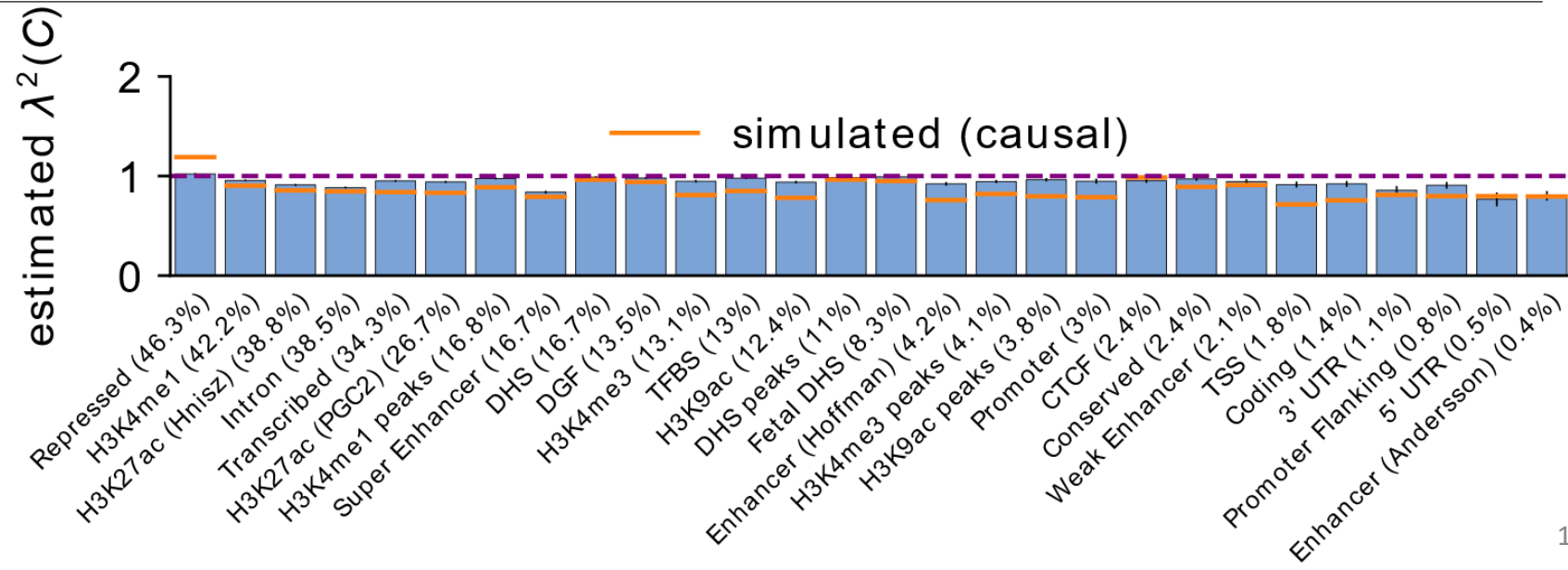
- Quintiles of continuous-valued annotations
(Gazal et al. 2017 *Nat Genet*)

estimates are shrunk towards the null: $\lambda^2(C)=1$



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Outline

- Method to stratify trans-ethnic genetic correlation (S-LDXR)
- **Analysis of 30 complex diseases and traits**
- Interpretation: potential role of positive selection

Analysis of 30 complex diseases and traits

- We obtained GWAS Summary statistics from

**East Asian
(N ≈ 93K)**

Biobank Japan (Kanai et al. 2018 *Nat Genet*)



**European
(N ≈ 274K)**

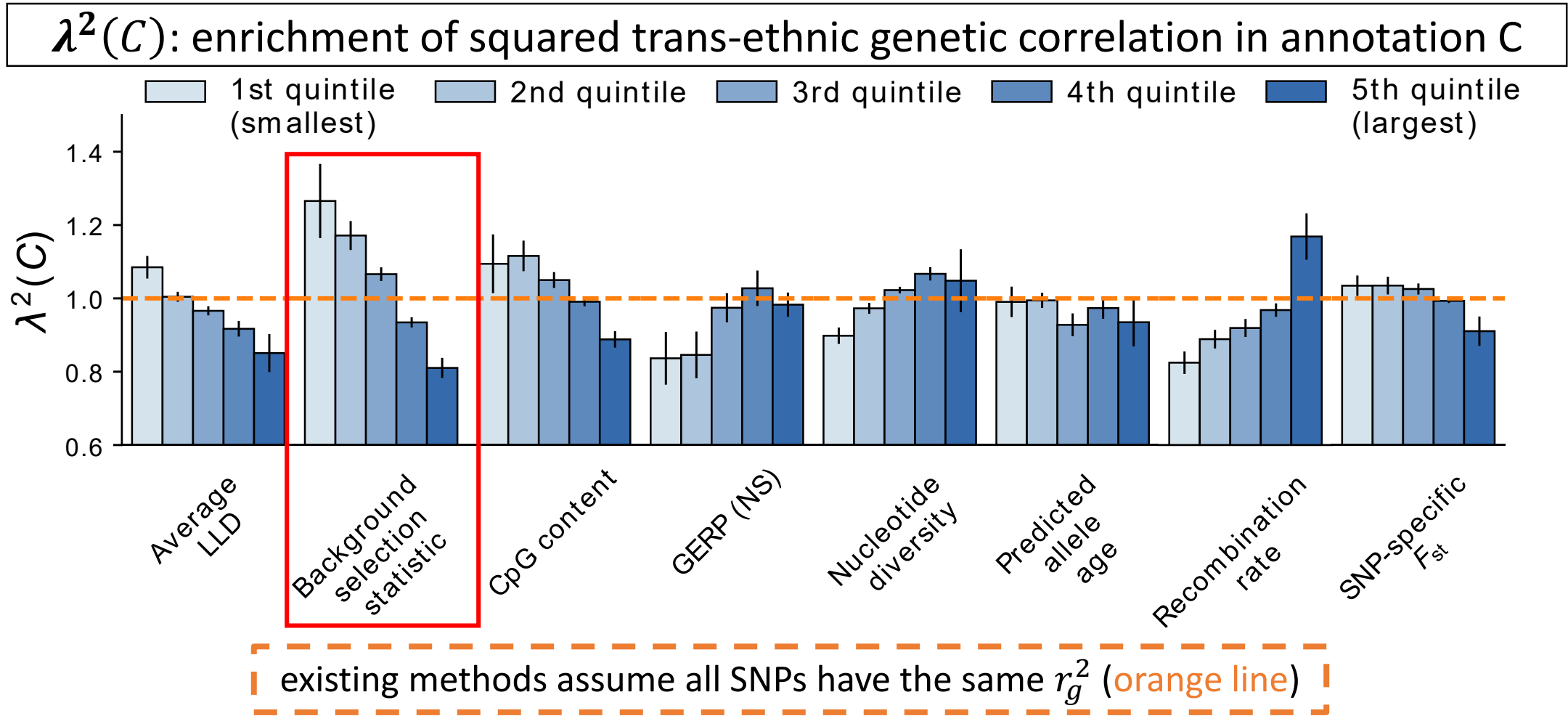
UK Biobank (Bycroft et al. 2018 *Nature*)



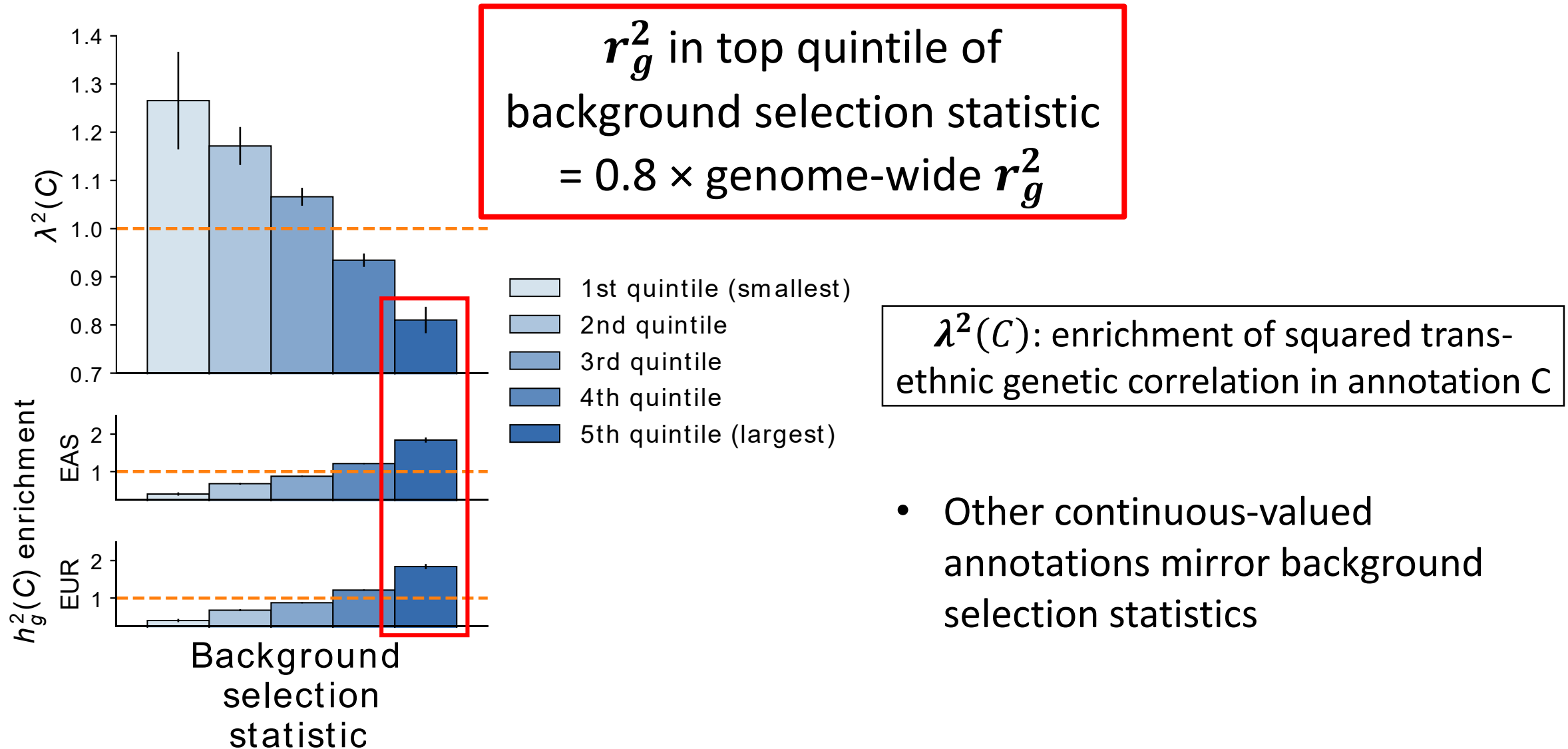
The method can be generalized to analyze other populations.

Trans-ethnic genetic correlation is depleted in top quintile of background selection statistic

- 8 continuous-valued annotations (Gazal et al. 2017 *Nat Genet*)



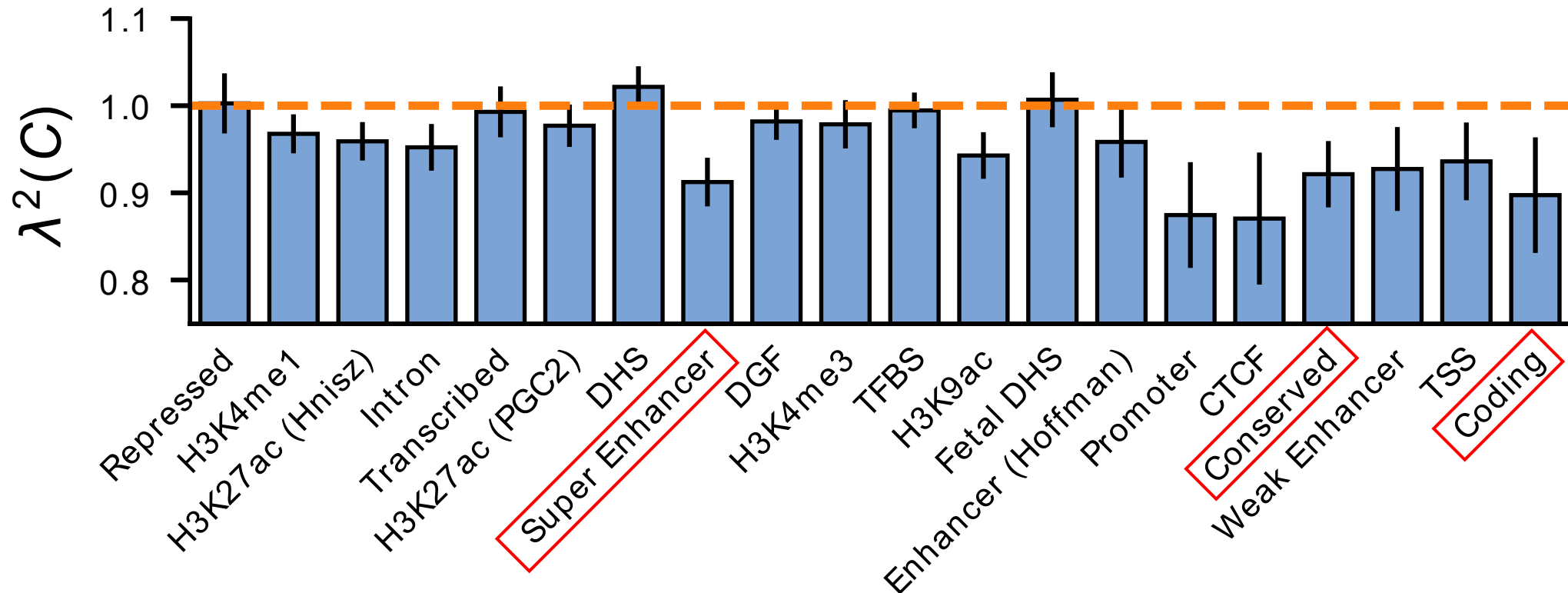
Trans-ethnic genetic correlation is depleted in top quintile of background selection statistic



Trans-ethnic genetic correlation is depleted in functionally important regions

$\lambda^2(C) < 1$ for most functional annotations

$\lambda^2(C)$: enrichment of squared trans-ethnic genetic correlation in annotation C

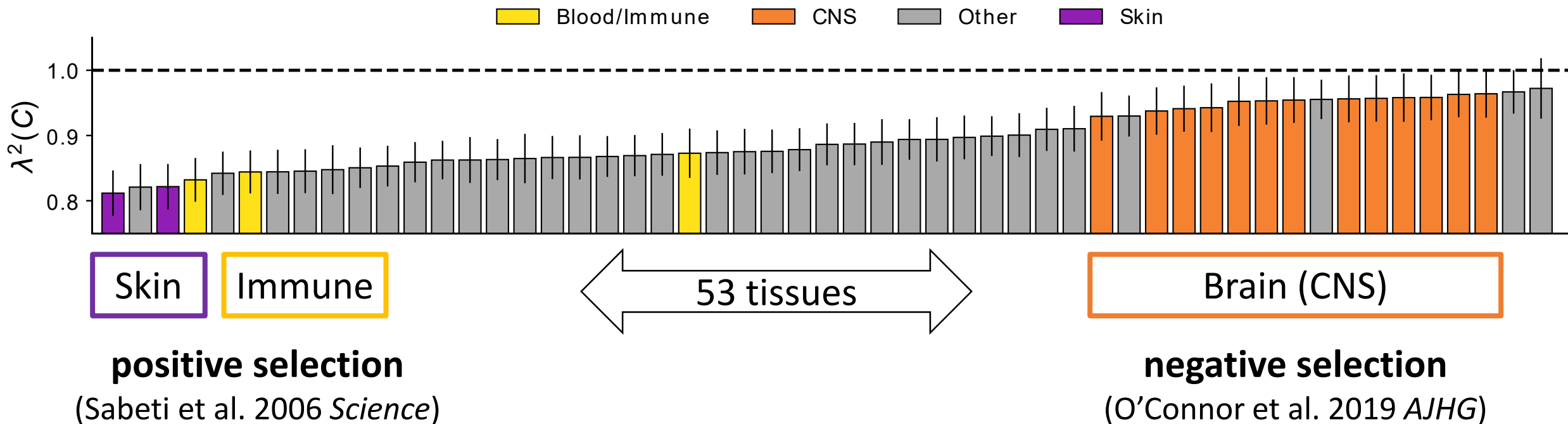


- Positively correlate with background selection statistic, enriched for heritability (Finucane et al. 2015 *Nat Genet*; Gazal et al. 2017 *Nat Genet*)

Trans-ethnic genetic correlation is most depleted near skin and immune genes and least depleted near brain genes

- Top 10% genes (± 100 kb) specifically expressed in 53 tissues (Finucane et al. 2018 *Nat Genet*)

$\lambda^2(C)$: enrichment of squared trans-ethnic genetic correlation in annotation C



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Interpretation: potential role of positive selection

- Trans-ethnic genetic correlation is depleted in functionally important regions.
- This is likely due to stronger G x E. (Robinson et al. 2017 *Nat Genet*) Dominance and G x G are less likely. (Hill et al. 2008 *Plos Genet*; Zhu et al. 2015 *AJHG*)
- Results for immune and skin genes suggest G x E may be linked to positive selection.

Acknowledgments

Also thanks to:

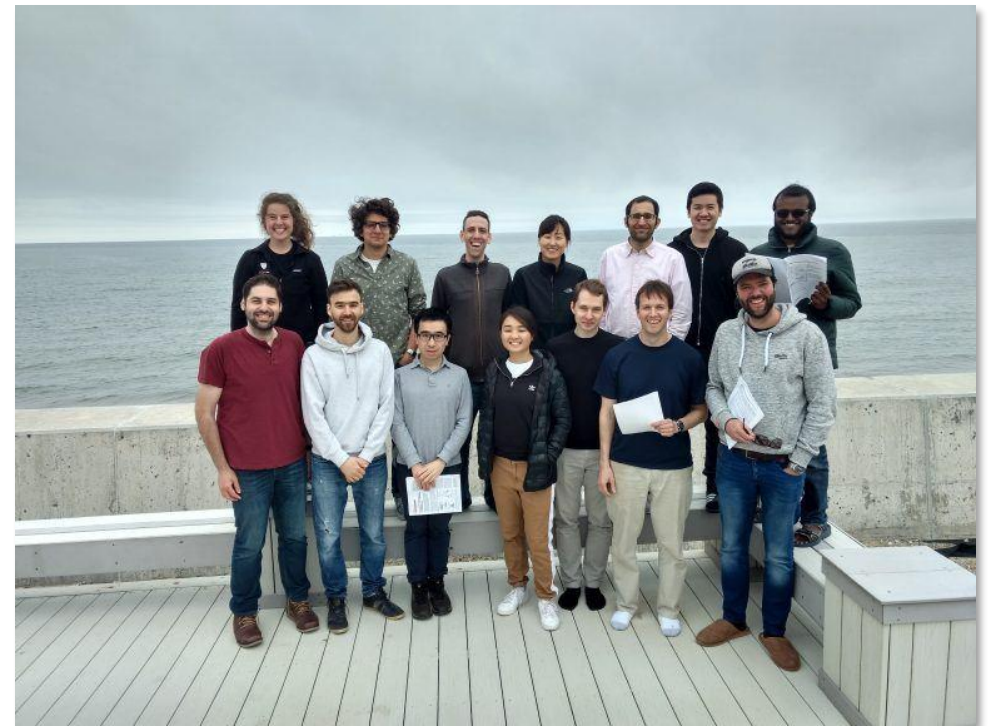
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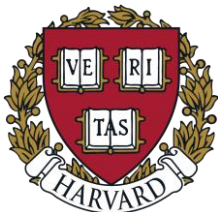
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(Shi et al. 2019 *bioRxiv*)



(journal club retreat, May 2019)



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