

# Genome-wide polygenic scores for common diseases identify individuals with risk equivalent to monogenic mutations

Amir V. Khera et al., Nature Genetics (2019)

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If we could identify people at high risk of developing a disease, we could **screen** them and encourage **prevention**.

Since common disease usually have an important genetic component, **DNA sequencing** can (hopefully!) help us.

# Disease genetics used to be easy...



Figure: Queen Victoria (1819-1901)

**Haemophilia** is a rare disease caused by a **single mutation** leading to low levels of clotting factors.

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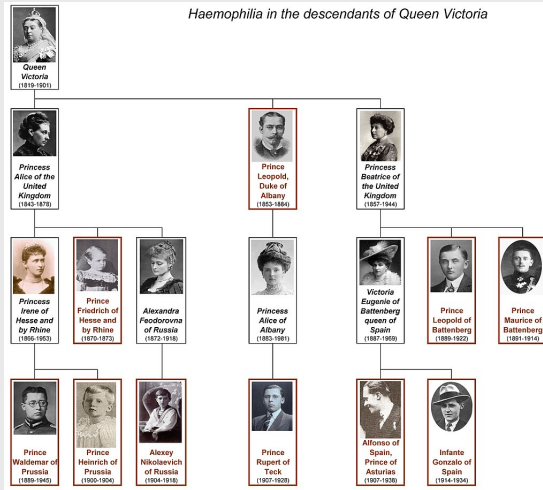


Figure: Haemophilia in Queen Victoria's descendants

Most **common diseases** are far more complex, depending on many genes and interactions with the environment.

Although some rare mutations with high impact have been found, the combined effect of **many common genetic variants**, each of small effect, is more important.

Even though complex diseases are hard...

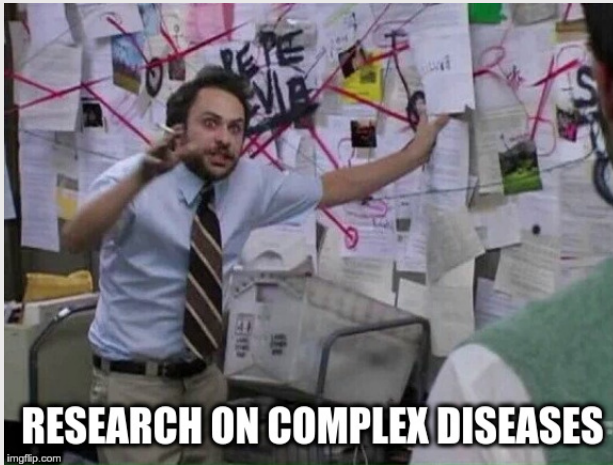


Figure: Meme

## ...polygenic scores might help

While

- ▶ we may not know which associated variants are **causal**
- ▶ the biological **pathways** may still be unclear

by looking at **many SNPs simultaneously** we might be able to accurately assess risk.

## **Advantages of polygenic scores:**

- ▶ can be calculated for many diseases simultaneously
- ▶ can be assessed from time of birth



# Genome-wide polygenic scores (GPS)

$$\begin{aligned}\text{GPS} = & \text{Weight}_1 \cdot \text{Mutation 1 indicator} + \\ & \text{Weight}_2 \cdot \text{Mutation 2 indicator} + \\ & \dots + \\ & \text{Weight}_p \cdot \text{Mutation } P \text{ indicator} +\end{aligned}$$

Need to identify relevant **variables** and compute **weights**.

# But GPSs don't work very well...

So far, GPSs have had **limited success** (for example identifying 20% of the population with a 1.4-fold higher risk).

Why?

- ▶ **small datasets** (both for building and testing scores)
- ▶ **methods** not good enough

# This paper

Try to improve the performance of GPSs by:

- ▶ using the results of **large recent GWAS studies**
- ▶ trying a **new method** (LDPred)

# This paper

Focus on 5 diseases:

- ▶ coronary artery disease (CAD)
- ▶ atrial fibrillation
- ▶ type 2 diabetes (T2D)
- ▶ inflammatory bowel disease (IBD)
- ▶ breast cancer

Over **700 000 observations** in total.

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4. iterate across all significant SNPs

Obtain 24 candidate scores for each disease.



## ARTICLE

## Modeling Linkage Disequilibrium Increases Accuracy of Polygenic Risk Scores

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Figure: Paper from Alkes Price's group

## Motivation:

- ▶ P+T doesn't account for linkage disequilibrium well enough and discards informative markers
- ▶ maybe we can do better by modelling the genetic architecture more explicitly

# LDPred is Bayesian

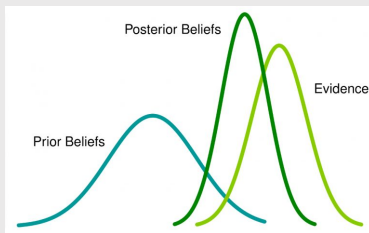


Figure: Bayes ♡

# Bayesian stats refresher

- ▶ All uncertainty is modelled through **probability distributions**
- ▶ Need **prior distributions** for model parameters
- ▶ **Bayes' Theorem** combines prior and data to give updated distribution of parameters:

$$\pi(\theta|\text{data}) \propto \text{Pr}(\theta) \cdot \text{Pr}(\text{data}|\theta)$$



**Figure:** Updating prior with evidence

## Advantages of the Bayesian approach:

- ▶ can incorporate **pre-existing knowledge** in an explicit and coherent way
- ▶ can make **probability statements** about parameters  
e.g. *“there’s a 70% chance that this parameter is greater than 0”*

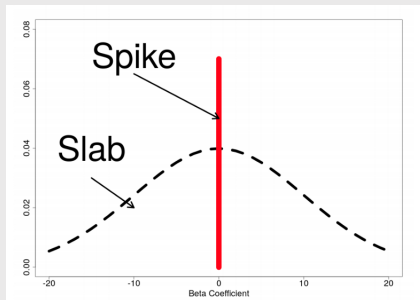


Figure: Spike-and-slab prior

Two parameters:

- ▶ fraction of causal markers
- ▶ heritability explained by genotypes

LDPred gives us the **expected value** (mean) for the effect of each SNP on the phenotype.

We use this to construct **7 GPSs** for different values of the parameter for fraction of causal markers.

Our two methods (P+T and LDPred) give us  $24 + 7 = 31$  candidate scores for each of the 5 diseases.

Use a first dataset (UKBB phase 1) to choose the best-performing model (AUC) for each disease (validation).

Use a second dataset (UKBB phase 2) to get a final assessment of performance for the selected models (testing).



# Results

- ▶ **CAD:** 8% of population with  $\geq 3$ -fold higher risk
- ▶ **Atrial fibrillation:** 6.1% with  $\geq 3$ -fold higher risk
- ▶ **T2D:** 3.5% with  $\geq 3$ -fold higher risk
- ▶ **IBD:** 3.2% with  $\geq 3$ -fold higher risk
- ▶ **Breast cancer:** 1.5% with  $\geq 3$ -fold higher risk, 0.1% with  $\geq 5 \times$

# Results

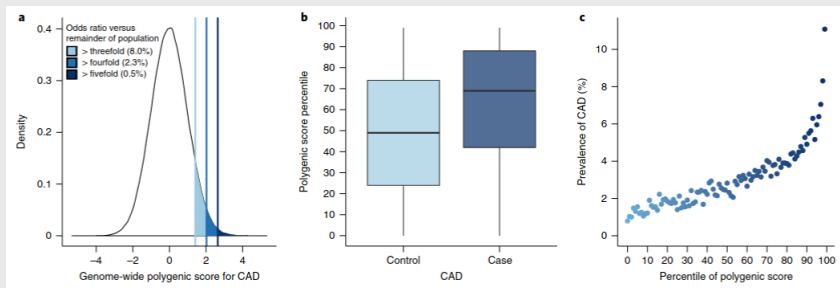


Figure: GPS for CAD

# Take away

*“Polygenic risk scores can now identify a substantially larger fraction of the population than is found by rare monogenic mutations, at comparable or greater disease risk.”*

# Big challenge

All this work was done with data from people of primarily **European ancestry**.

GPSs don't work nearly as well for **other ethnic groups**:

- ▶ different allele frequencies, LD patterns and SNP effect sizes

# Discussion

How can we **communicate** this type of results to patients?

Is it ever sensible and ethical to **withhold information**?

Should parents be able to choose whether to have their **children tested**?

How should we **allocate resources** between people with different levels of risk?

How should genetic risk stratification be integrated with **other (e.g. environmental) risk factors**?