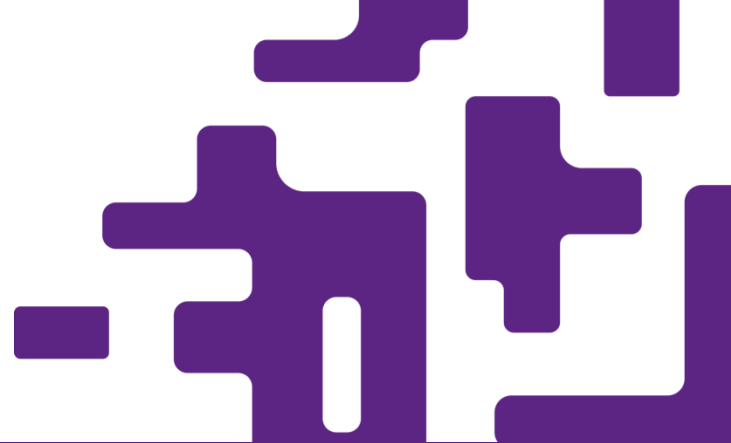




NORMENT

Norwegian Centre for
Mental Disorders Research



Introduction to genetics of complex traits

Oleksandr Frei

MIPT-NORMENT, October 21st, 2019

Introduction to genetics of complex traits

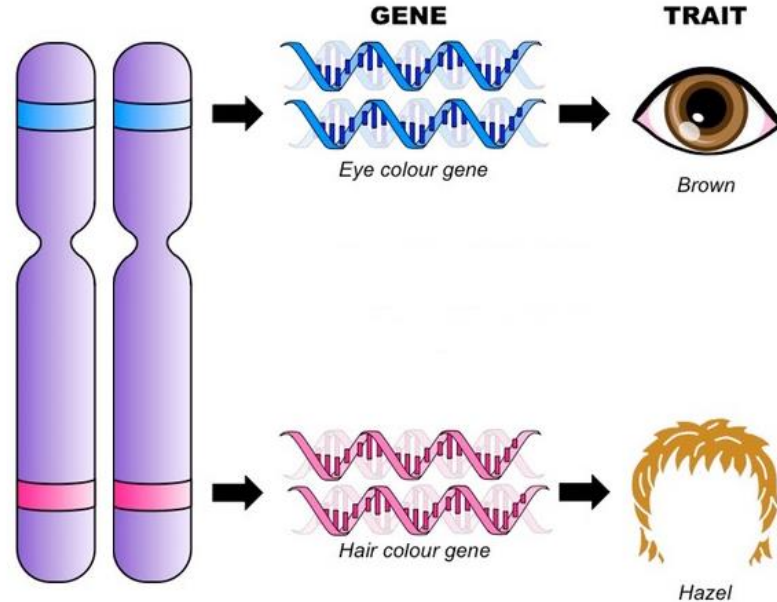
- **Genetics of Complex Traits**
 - Mendelian vs polygenic inheritance
 - Heritability, twin studies
 - Genome-wide association studies
- **Big Data samples**
 - GWAS consortia
 - TOP, MoBa (Norwegian samples)
 - UK Biobank, ABCD
- **Challenges and advanced in statistical analysis**
 - Correlation structure in the genotype matrix
 - Specific tools (conjFDR, MiXeR, MOSTest)

Introduction to genetics of complex traits

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Genes and their alleles

- ~24,000 genes in humans
- Most genes exist in many forms called **alleles** (A or a)
- Our cells have two alleles for each gene, one from each parent (AA, Aa, aa)



Huntington's disease

- Dominant inheritance

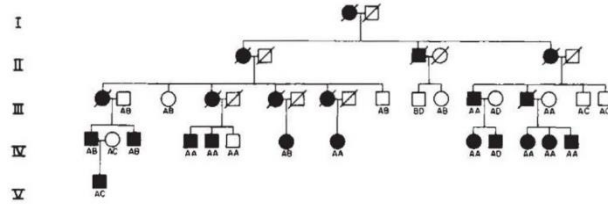
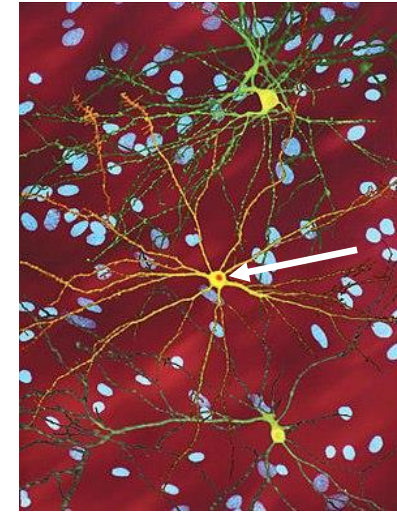


Fig. 1 Pedigree of an American Huntington's disease family.



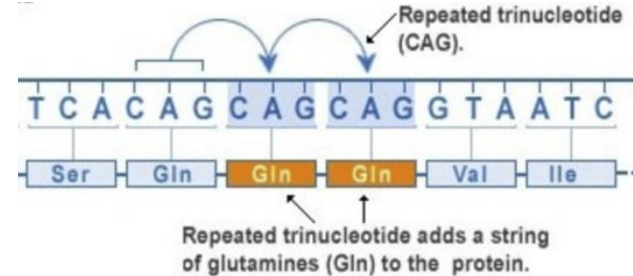
- Huntington Gene on chromosome 4



Article | Published: 17 November 1983

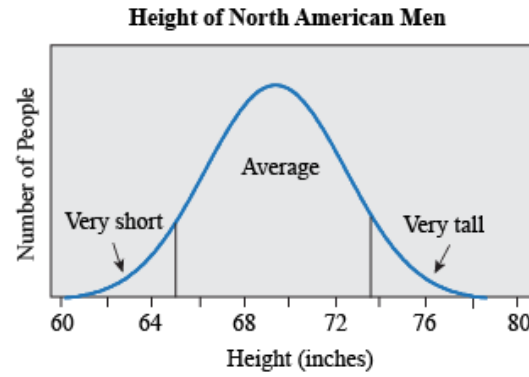
A polymorphic DNA marker genetically linked to Huntington's disease

An edited microscopic image of medium spiny neurons(yellow) with nuclear inclusions (orange), which occur as part of the disease process

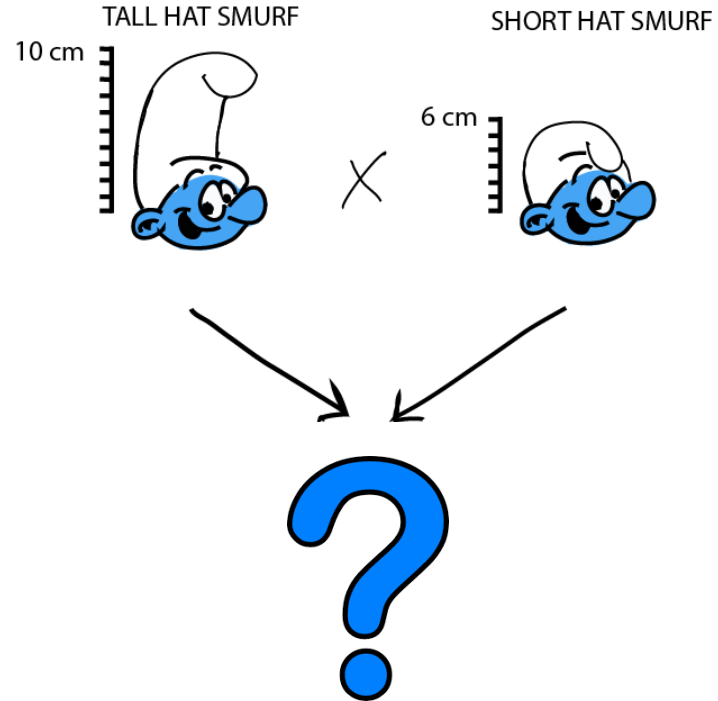


Quantitative genetics: complex traits

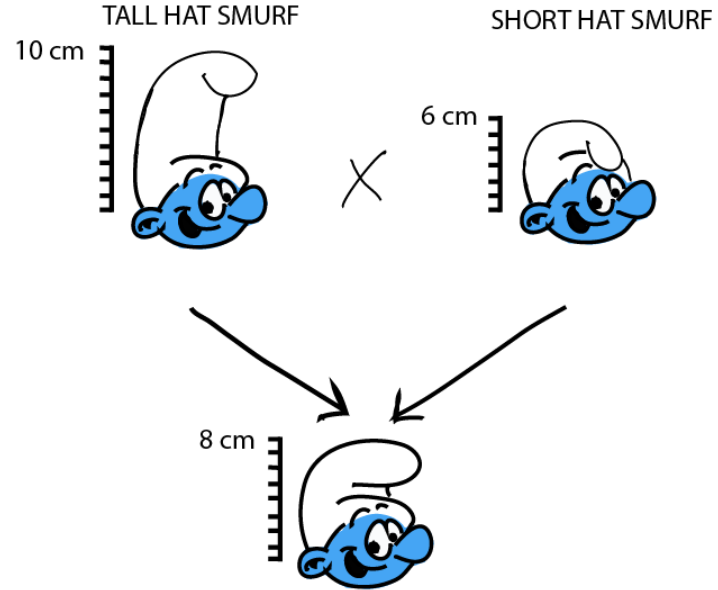
- Most traits are not discrete
- Height is a great example, can range from 74.6 cm (He Pingping) to 272 cm (Robert Pershing Wadlow)
- This also applies to discrete traits such as Schizophrenia diagnosis: Liability (or predisposition) to the disorder is a complex genetic trait
- Many genes involved (“polygenic”)
- Effects of the environment



Additive effects of multiple genes



Additive effects of multiple genes



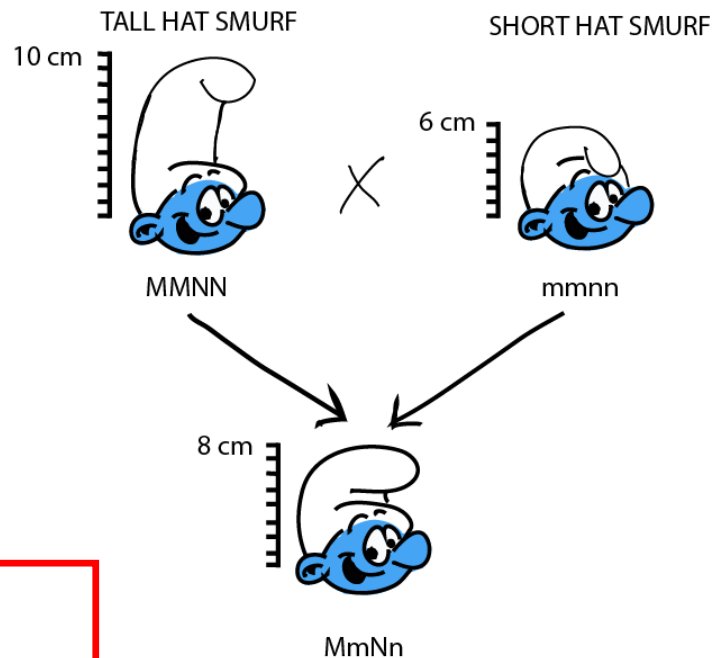
Additive effects of multiple genes

M: +3 cm

N: +2 cm

m: +2 cm

n: +1 cm

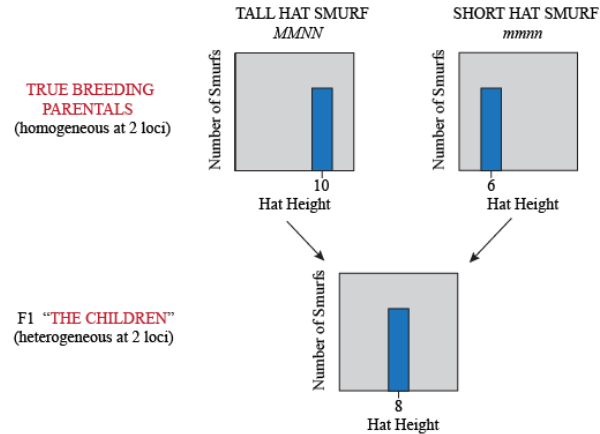


$$y_i = \sum_j w_{ij} u_j + e_i$$

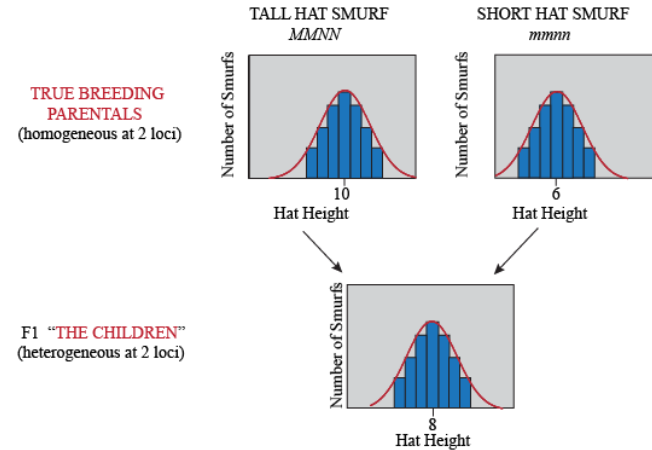
(simple additive genetic model)

Effects of the environment

Assume no environmental effects:



Adding the effect of environment:



Heritability

- Heritability represents the proportion of the phenotypic variation in a population that is explained by genetic factors
- For example, how is intelligence in people determined? Did someone with a high IQ just inherit it from her parents, or does stimulation while growing up make a difference too?

Broad-sense heritability:

$$V_P = V_G + V_E$$

$$H^2 = V_G/V_P$$

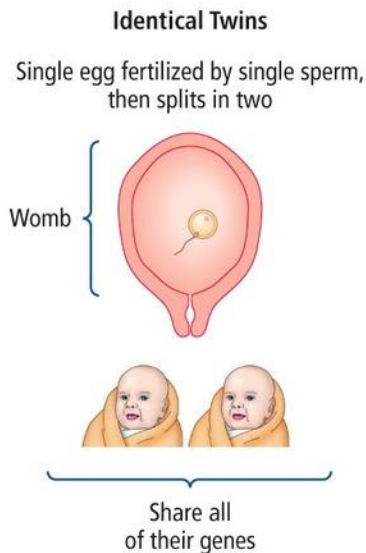
Narrow-sense heritability:

$$V_P = (V_A + V_D + V_I) + V_E$$

$$h^2 = V_A/V_P$$

Twin studies

- Monozygotic (MZ) twins were conceived in a single egg, which later split
- Dizygotic (DZ) twins were conceived when two or more eggs were fertilised at the same time



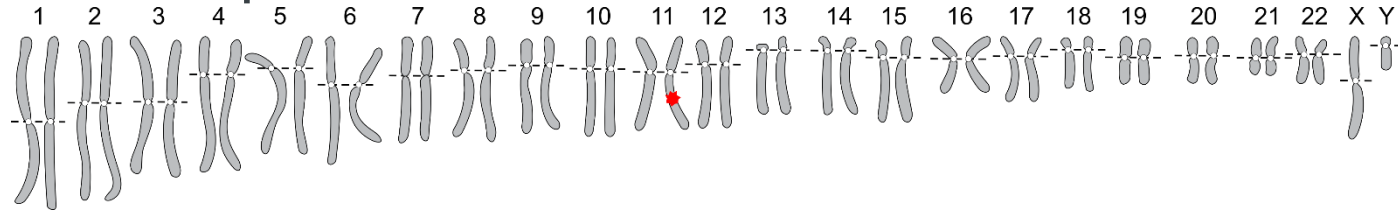
Genes or environment?

- A famous example would be the Genain quadruplets. Born in 1930, these identical (MZ) German sisters all developed schizophrenia, which suggests a "schizophrenic gene" is at work. The mother and father also had family histories of mental illness, which adds to the credibility of the theory that schizophrenia is at least partly due to genetical factors.

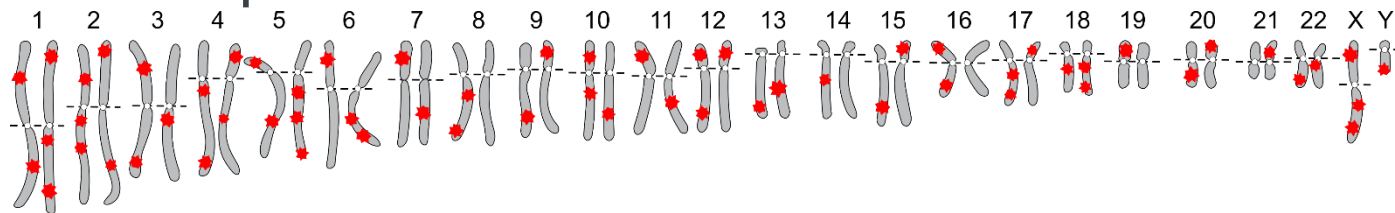


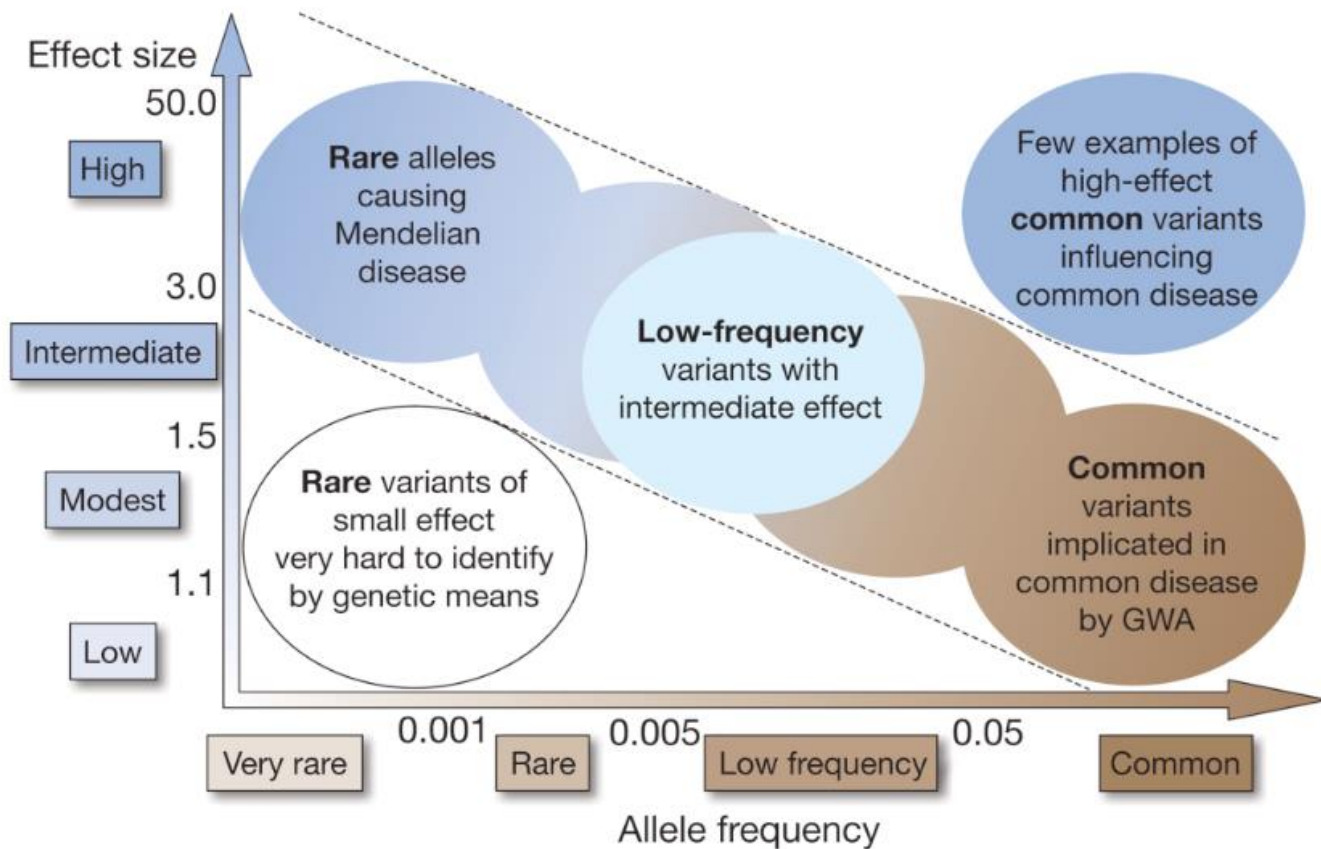
- Schizophrenia heritability: 80-90%
- Schizophrenia concordance rates:
 - 40-50% MZ twins
 - 4% DZ twins

Complex traits and GWAS

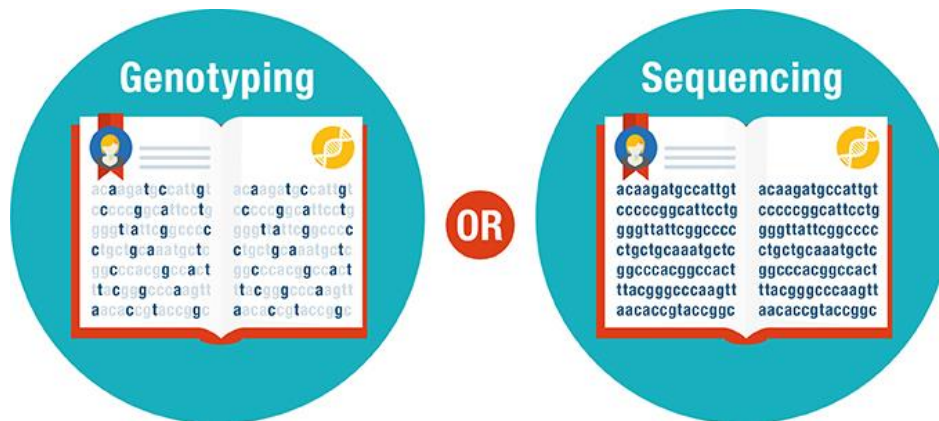


Complex traits and GWAS

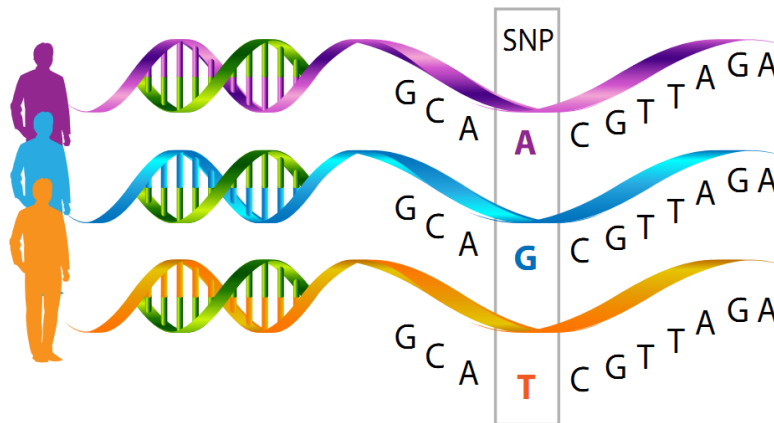




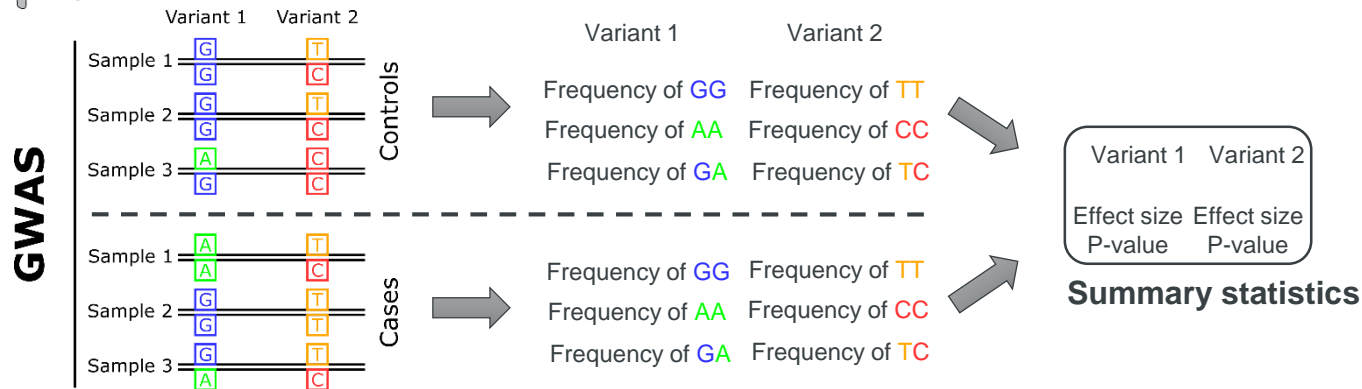
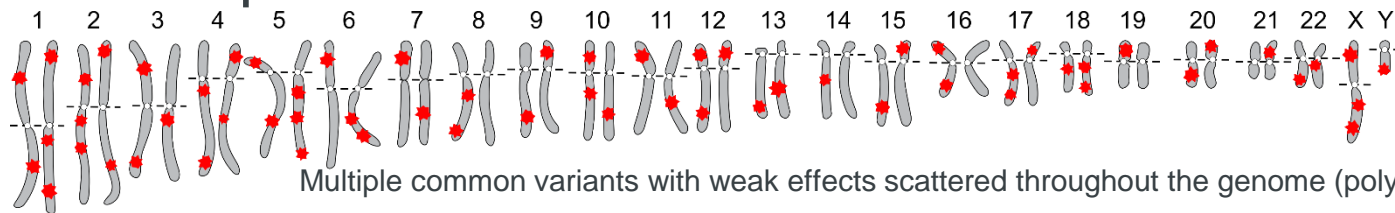
Sequencing and genotyping technologies



approx. 10 million
common SNPs
(frequency above 0.5%)



Complex traits and GWAS



Input data for GWAS analysis

Input:

N attributes (3-category), 1 binary class variable

M samples

	SNP ₁	SNP ₂	...	SNP _n	Class
Patient ₁	1	1	...	0	1
Patient ₂	0	2	...	1	0
Patient ₃	1	0	...	2	1
...					
Patient _M	2	1	...	1	0

Output:

SNPs associated with diseases
1- order: {SNP₁}, {SNP₂}, {SNP₃}...
2-order : {SNP₁, SNP₂}...
3-order : {SNP₁, SNP₂, SNP₃}...

Encoding:

- AA -> 0, Aa -> 1, aa -> 2
- Case -> 1, Control -> 0

Biological insights from 108 schizophrenia-associated genetic loci

Schizophrenia Working Group of the Psychiatric Genomics Consortium*

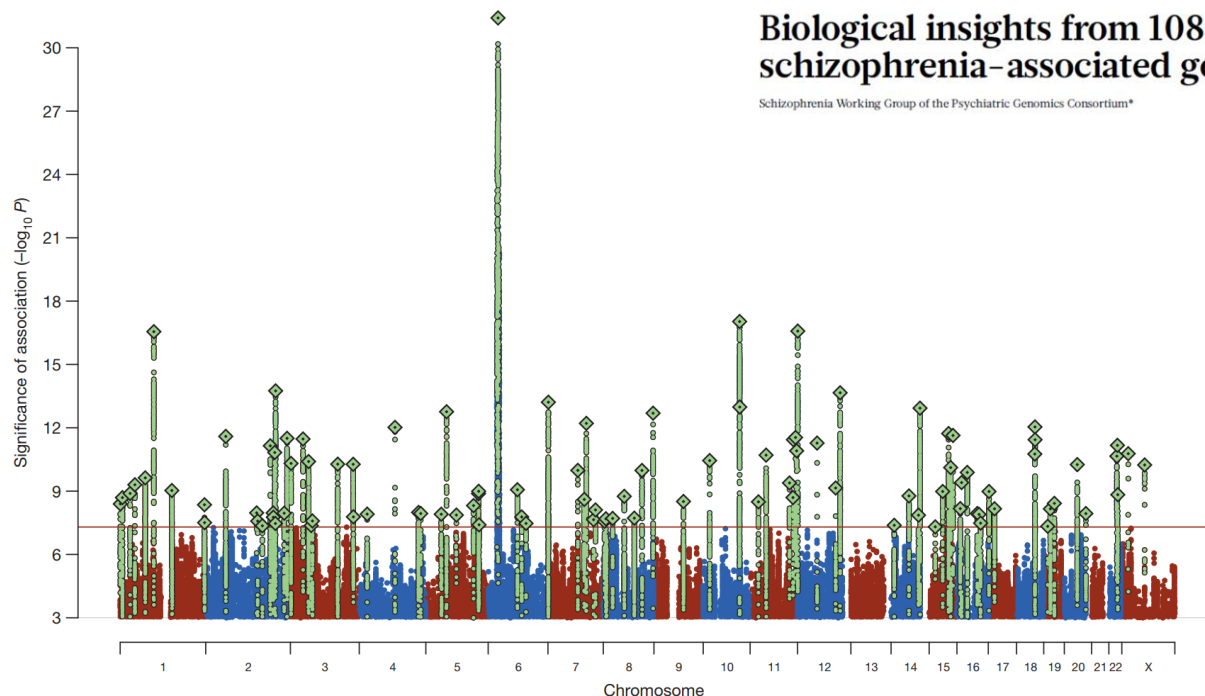


Figure 1 | Manhattan plot showing schizophrenia associations. Manhattan plot of the discovery genome-wide association meta-analysis of 49 case control samples (34,241 cases and 45,604 controls) and 3 family based association studies (1,235 parent affected-offspring trios). The x axis is chromosomal

position and the y axis is the significance ($-\log_{10} P$; 2-tailed) of association derived by logistic regression. The red line shows the genome-wide significance level (5×10^{-8}). SNPs in green are in linkage disequilibrium with the index SNPs (diamonds) which represent independent genome-wide significant associations.

Supplementary Table 2: 128 genome-wide significant associations for schizophrenia

Rank	Index SNP	A12	Frq _{case}	Frq _{control}	Chr	Position	Combined		Discovery	Replication		
							OR (95% CI)	P		OR	P	
54	rs4648845	TC	0.533	0.527	1	2,372,401-2,402,501	1.072 (1.049-1.097)	8.7e-10	1.071	4.03e-9	1.088	8.85e-2
57	chr1_8424984_D	I2D	0.319	0.301	1	8,411,184-8,638,984	1.071 (1.048-1.095)	1.17e-9	1.071	2.03e-9	1.057	2.96e-1
65	rs1498232	TC	0.311	0.296	1	30,412,551-30,437,271	1.069 (1.046-1.093)	2.86e-9	1.072	1.28e-9	0.999	9.88e-1
50	rs11210892	AG	0.659	0.677	1	44,029,384-44,128,084	0.934 (0.914-0.954)	3.39e-10	0.933	4.97e-10	0.949	3.08e-1
22	rs12129573	AC	0.377	0.358	1	73,766,426-73,991,366	1.078 (1.056-1.101)	2.03e-12	1.072	2.35e-10	1.217	6.25e-5
107	rs76869799	CG	0.959	0.964	1	97,792,625-97,834,525	0.846 (0.798-0.897)	2.64e-8	0.850	1.44e-7	0.779	5.34e-2
2	rs1702294	TC	0.175	0.191	1	98,374,984-98,559,084	0.887 (0.865-0.911)	3.36e-19	0.891	2.79e-17	0.831	1.35e-3
52	rs140505938	TC	0.151	0.164	1	149,998,890-150,242,490	0.914 (0.888-0.940)	4.49e-10	0.913	9.34e-10	0.928	2.53e-1
120	rs6670165	TC	0.196	0.184	1	177,247,821-177,300,821	1.075 (1.047-1.103)	4.45e-8	1.074	1.16e-7	1.090	1.46e-1
121	rs7523273	AG	0.695	0.685	1	207,912,183-208,024,083	1.063 (1.040-1.087)	4.47e-8	1.062	1.61e-7	1.092	8.85e-2
101	rs10803138	AG	0.232	0.238	1	243,503,719-243,612,019	0.933 (0.911-0.956)	2.03e-8	0.932	1.79e-8	0.968	5.56e-1
68	rs77149735	AG	0.0225	0.0191	1	243,555,105-243,555,105	1.317 (1.202-1.444)	3.73e-9	1.329	4.4e-9	1.173	3.66e-1
119	rs14403	TC	0.207	0.222	1	243,639,893-243,664,923	0.934 (0.911-0.957)	4.42e-8	0.935	1.31e-7	0.920	1.53e-1
78	chr1_243881945_I	I2D	0.638	0.619	1	243,690,945-244,002,945	1.068 (1.045-1.092)	6.53e-9	1.066	3.11e-8	1.107	6.17e-2
30	rs11682175	TC	0.52	0.542	2	57,943,593-58,065,893	0.933 (0.914-0.952)	1.47e-11	0.928	2.54e-12	1.018	7.08e-1
117	rs75575209	AT	0.904	0.913	2	58,025,192-58,502,192	0.902 (0.869-0.936)	3.95e-8	0.896	1.01e-8	1.056	5.6e-1
80	rs3768644	AG	0.0967	0.101	2	72,357,335-72,368,185	0.904 (0.874-0.935)	7.39e-9	0.910	1.3e-7	0.765	2.15e-3
62	chr2_146436222_I	I2D	0.176	0.163	2	146,416,922-146,441,832	1.086 (1.057-1.116)	1.81e-9	1.084	1.07e-8	1.128	5.72e-2
95	chr2_149429178_D	I2D	0.955	0.961	2	149,390,778-149,520,178	0.857 (0.813-0.904)	1.59e-8	0.856	2.62e-8	0.880	2.97e-1
124	rs2909457	AG	0.568	0.593	2	162,798,555-162,910,255	0.944 (0.925-0.964)	4.62e-8	0.943	4.38e-8	0.971	5.36e-1
18	rs11693094	TC	0.44	0.458	2	185,601,420-185,785,420	0.929 (0.910-0.948)	1.53e-12	0.929	7.13e-12	0.918	7.64e-2
83	rs59979824	AC	0.322	0.337	2	193,848,340-194,028,340	0.937 (0.916-0.958)	8.41e-9	0.936	1.08e-8	0.959	4.32e-1
33	rs6434928	AG	0.635	0.643	2	198,148,577-198,835,577	0.929 (0.909-0.949)	2.06e-11	0.927	1.48e-11	0.969	5.36e-1
82	rs6704641	AG	0.819	0.805	2	200,161,422-200,309,252	1.081 (1.053-1.110)	8.33e-9	1.079	3.4e-8	1.123	8.1e-2
10	chr2_200825237_I	I2D	0.741	0.754	2	200,715,237-200,848,037	0.909 (0.887-0.932)	5.65e-14	0.906	1.78e-14	1.011	8.7e-1
87	rs11685299	AC	0.313	0.326	2	225,334,096-225,467,796	0.939 (0.919-0.959)	1.12e-8	0.937	1.11e-8	0.974	6.12e-1
23	rs6704768	AG	0.54	0.552	2	233,559,301-233,753,501	0.930 (0.911-0.949)	2.32e-12	0.929	3.15e-12	0.953	3.19e-1

GWAS aims to find genetic effects => PRS

Input (known):

y_i – phenotypes

w_{ij} – genotypes

10 cm



MMNN

6 cm



mmnn

8 cm



MmNn

Output (unknown):

\hat{u}_j - genetic effects of
allele substitution

M: +? cm

N: +? cm

m: +? cm

n: +? cm

$$\hat{y}_i = \sum_j w_{ij} \hat{u}_j + e_i$$

Polygenic Risk Scoring, or
Naïve Bayes classifier

Introduction to genetics of complex traits

- **Genetics of Complex Traits**
 - Mendelian vs polygenic inheritance
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 - TOP, MoBa (Norwegian samples)
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 - Correlation structure in the genotype matrix
 - Specific tools (conjFDR, MiXeR, MOSTest)

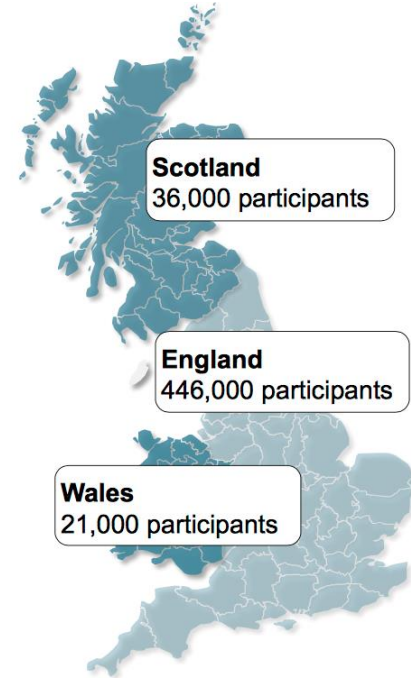
Big data NORMENT

- Clinical samples
 - Hospitals n=25k (Psychosis, dementia, ASD etc)
- Population genetics (prospective, registries):
 - MoBa n=240k (100k kids, parents)
 - HUSK n=36k (cohort)
 - HUNT n=70k (collaboration)
 - Tromsø Study n=35k (cohort, 2019)
- Total n=400k
- Other samples: 550k



NORMENT In-house Data

- N = 500k
- Aged 40-69 recruited between 2006 and 2010
- Genetic data (500k genotype, 50k whole-exome sequence)
- Registry-based information
- Extensive self-reported baseline data on lifestyle environment, personal & family medical history, including detailed mental health questionnaire
- Brain imaging data ~45k



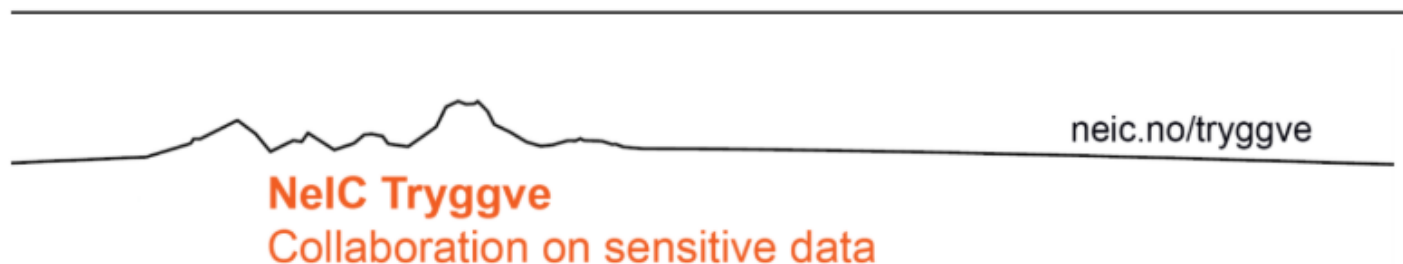
NORMENT In-house Data

- N ~ 12k
- Aged 9-10 at recruitment
- Will be followed up through early adulthood
- Genetic data
- Extensive self-reported baseline data on lifestyle, environment, personal & family medical history, including detailed mental health questionnaire
- Brain imaging data - all
- Wait for phenotypes to develop - longitudinal, prospective

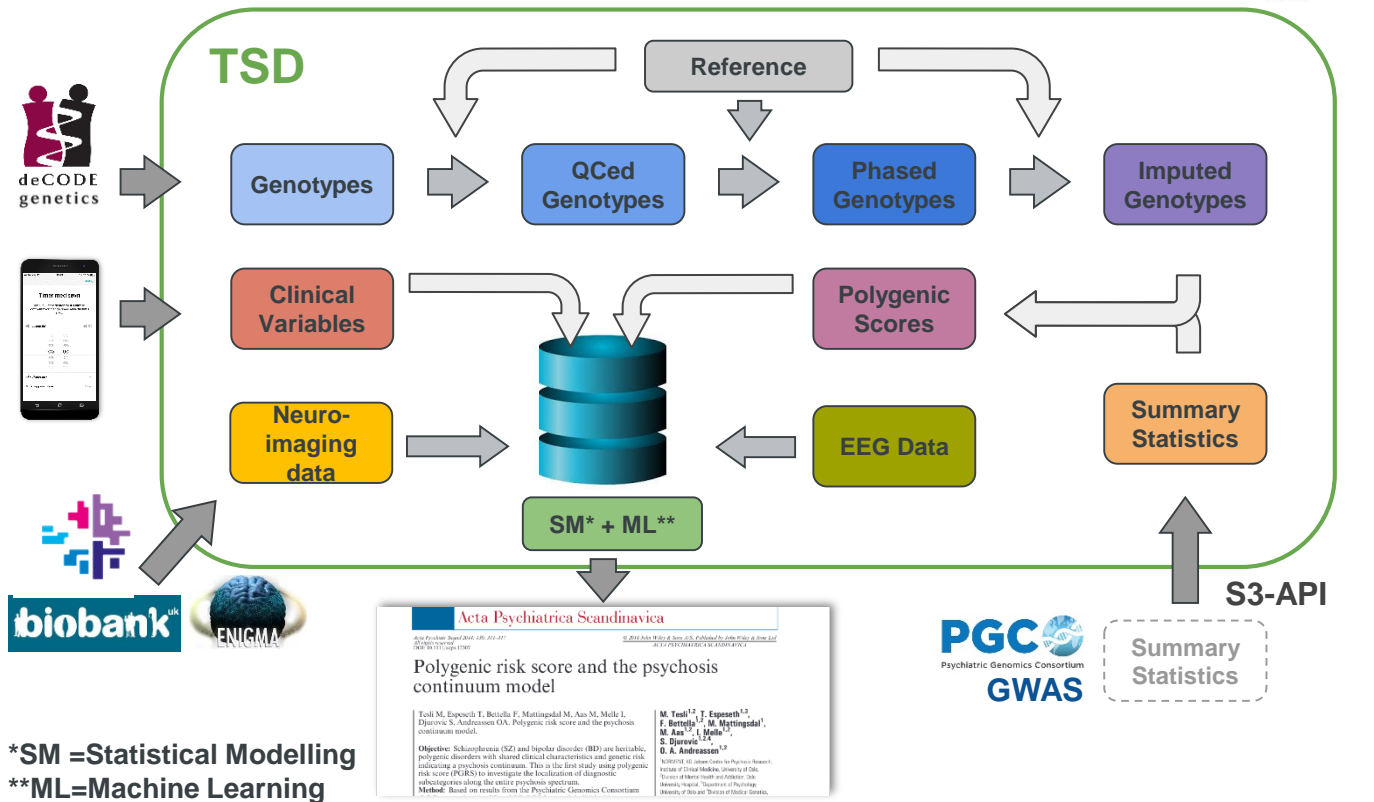


Data Sensitivity

- Most sensitive individual data
 - Individual identification
 - Privacy around mental health status
- All data stored and analyzed on secure computing cluster (TSD)
 - Individual level data anonymized and cannot be exported
- *TRYGGVE* - data sharing across Nordic countries



The NORMENT Big Data pipeline



*SM =Statistical Modelling

**ML=Machine Learning

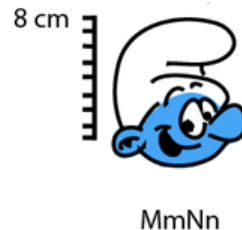
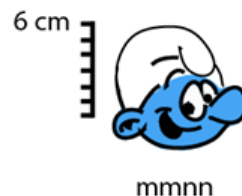
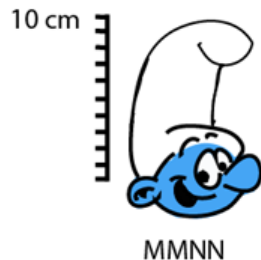
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What's so challenging?

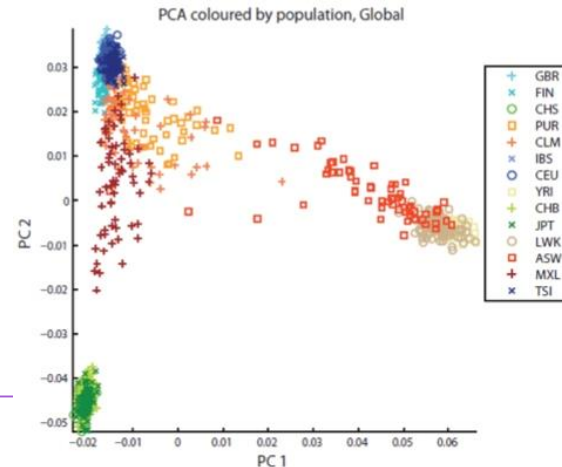
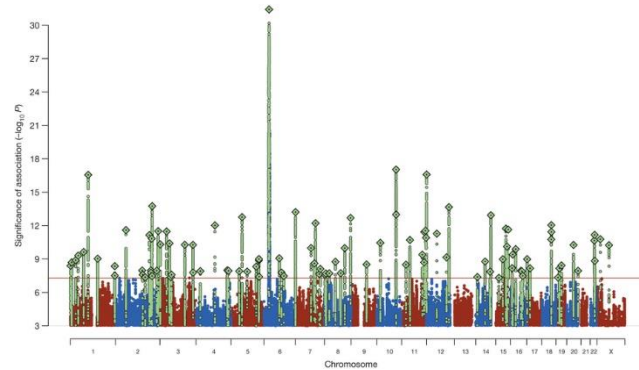
$$y = Gx + \epsilon$$

- y - phenotype vector
- G - genotype matrix
- x - unknown genetic effects
- ϵ - environmental noise



Challenges in GWAS analysis

- “BigData” scale:
 - 10^7 genetic variants (SNPs)
 - 10^6 individuals
- Correlation structure:
 - Relatedness among individuals
 - “Linkage disequilibrium” in SNPs
- Heterogeneity in GWAS cohorts
 - Different populations
 - Potential overlap between cohorts
- Statistical power
 - Small individual effects
 - ca. 1 000 000 independent tests, multiple hypothesis correction
 - => typical p-value threshold 5×10^{-8}



Models to estimate heritability from genotype data

- Mixed effects model

$$y = g + X\beta + \epsilon$$

Phenotype

Genetic component

Clinical covariates (Age, sex, ...) Fixed effects

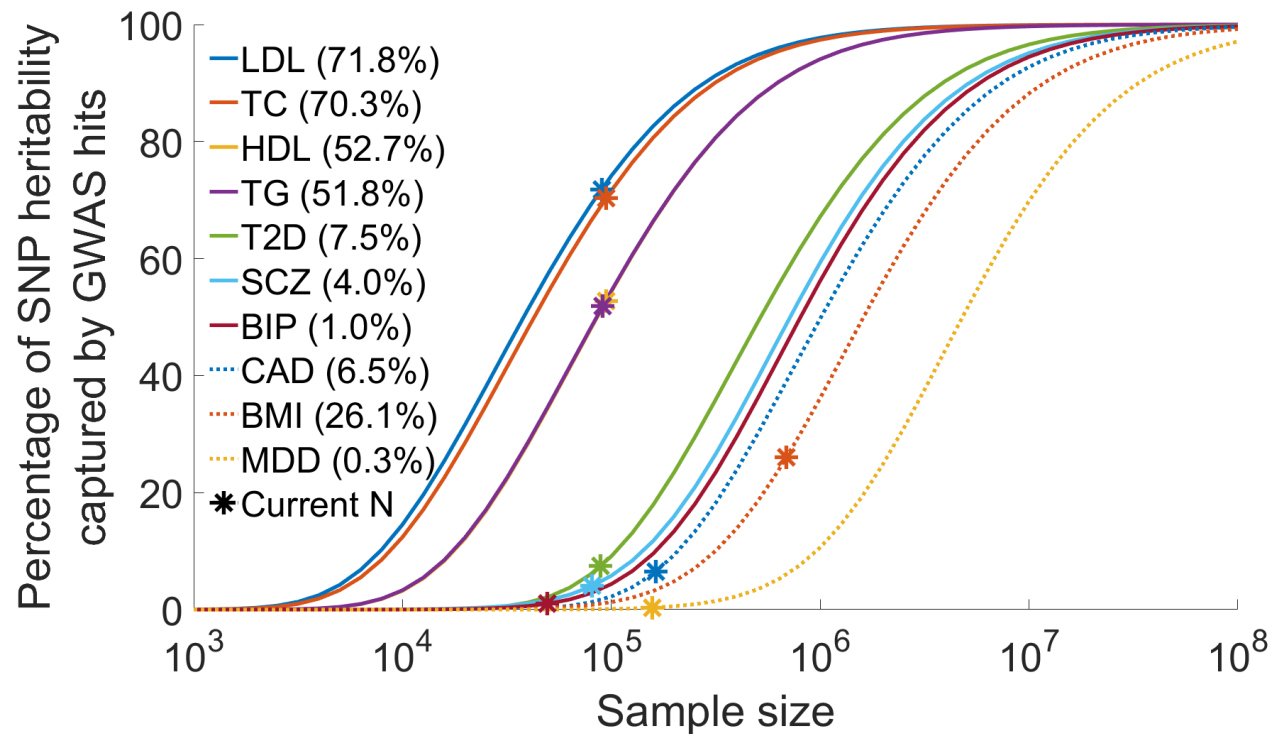
Unmeasured contribution from the environment

$g \sim N(0, A\sigma_g^2)$
random effects,
 A is derived from W

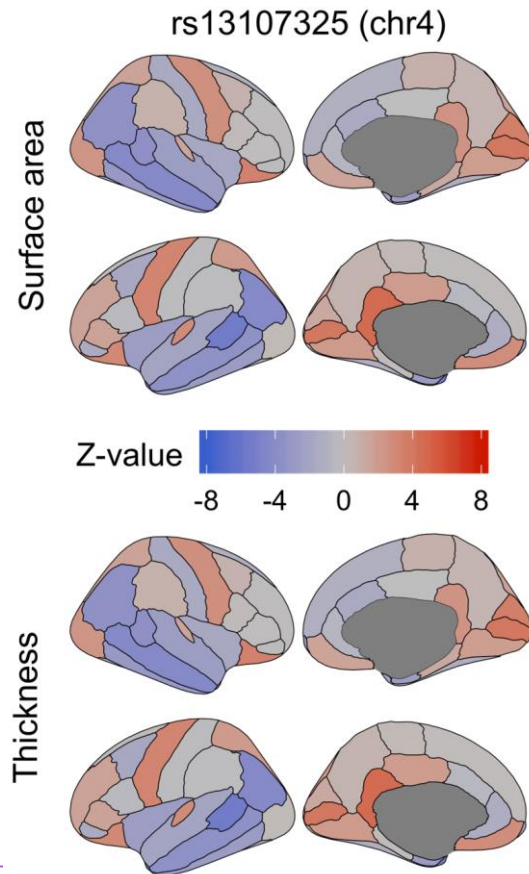
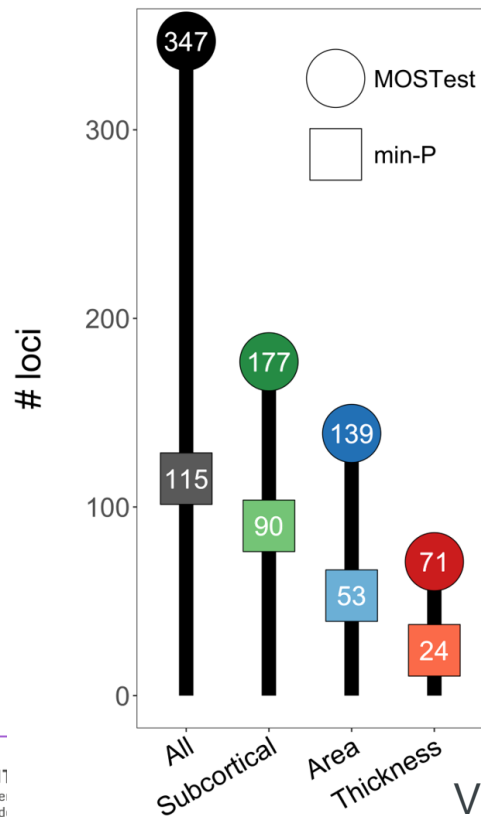
GCTA - Restricted maximum likelihood (RELM) [Patterson and Thompson, 1971] [Harville, 1974], Average Information (AI) inference [Arthur R. Gilmour, 1995]

BoltLMM – more efficient inference with Monte Carlo REML approximation, conjugate gradient iteration to solve mixed model equations, Variational Bayes iteration

Polygenicity affects power to discover loci in GWAS



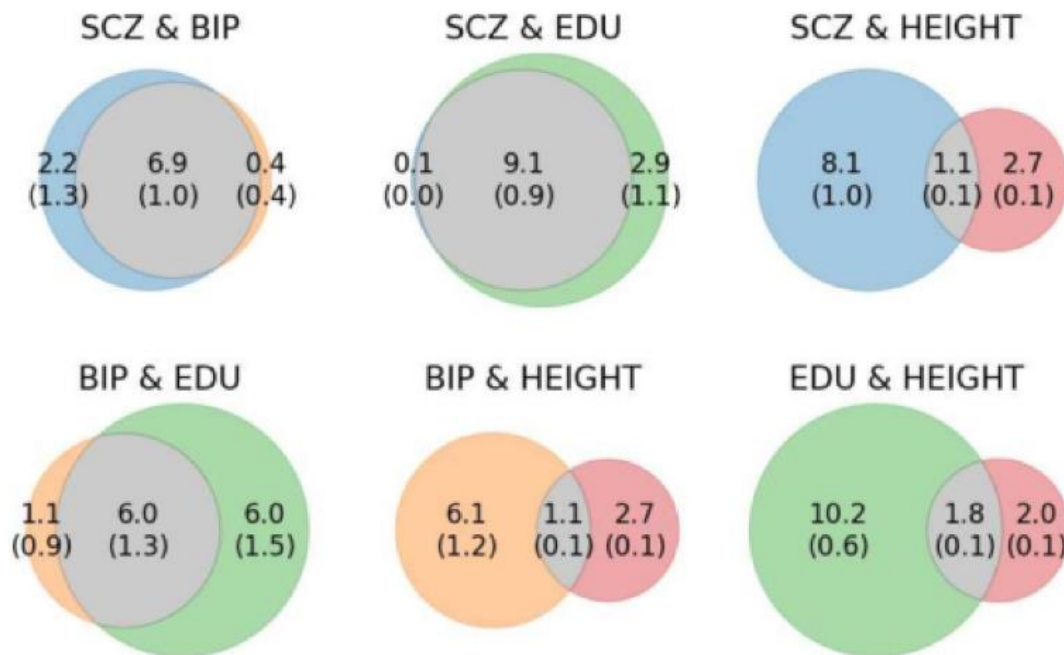
MOSTest – increase discovery (Multivariate Omnibus Statistical Test)



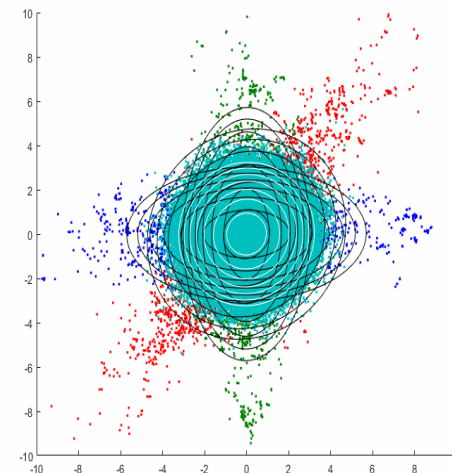
Polygenic overlap – mathematical modeling

Bivariate causal mixture model quantifies polygenic overlap between complex traits beyond genetic correlation

Oleksandr Frei, Dominic Holland, Olav B. Smeland, Alexey A. Shadrin, Chun Chieh Fan, Steffen Maeland, Kevin S. O'Connell, Yunpeng Wang, Srdjan Djurovic, Wesley K. Thompson, Ole A. Andreassen & Anders M. Dale



<https://github.com/precimed/mixer>



Extensive genetic overlap

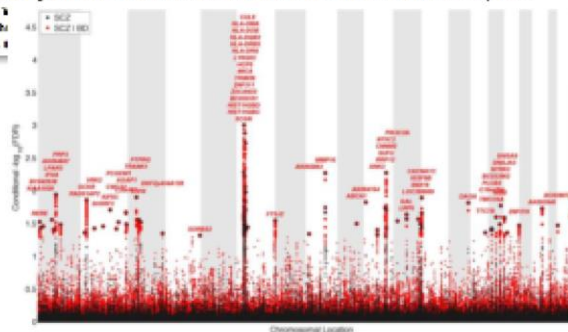
Conditional/conjunctive False Discovery Rate

OPEN ACCESS | Freely available online

PLOS | research

Improved Detection of Common Variants Associated with Schizophrenia and Bipolar Disorder Using Pleiotropy-Informed Conditional False Discovery Rate

Ole A. Andreassen^{1,2,3,4}, Wendy K. Thompson⁵, Andrew J. Schork^{1,2,3,4}, Stephan Ripke², Maarten Mattingly¹, John R. Kalsbeek⁶, Kenneth S. Kendler⁶, Michael C. O'Donovan⁵, Dan Rujescu⁷, Thomas A. Schizophrenia⁸, Hakul S. 8



51 novel SCZ loci

11 novel BIP loci

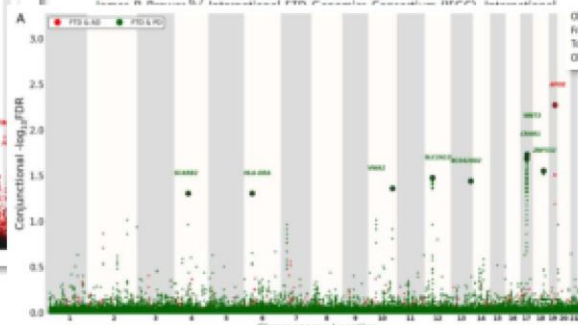
14 loci shared between SCZ and BIP

Neurogenetics

RESEARCH PAPER

Genetic architecture of sporadic frontotemporal dementia and overlap with Alzheimer's and Parkinson's diseases

Raffaële Ferrás¹, Yunpeng Wang², Jana Vandrowcova^{1,3}, Sebastian Gueff^{1,3}, Aree Witteolar², Celeste M. Kirch⁴, Andrew J. Schork⁵, Chun C. Fan⁵



8 loci shared between FTD and PD

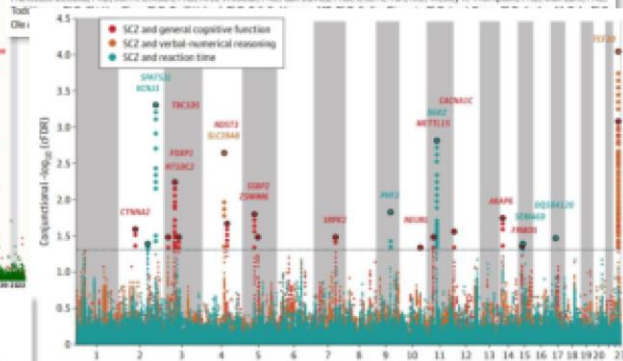
1 shared locus between FTD and AD

13 novel FTD loci

JAMA Psychiatry | Original Investigation

Identification of Genetic Loci Jointly Influencing Schizophrenia Risk and the Cognitive Traits of Verbal-Numerical Reasoning, Reaction Time, and General Cognitive Function

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21 loci shared between SCZ and cognitive traits

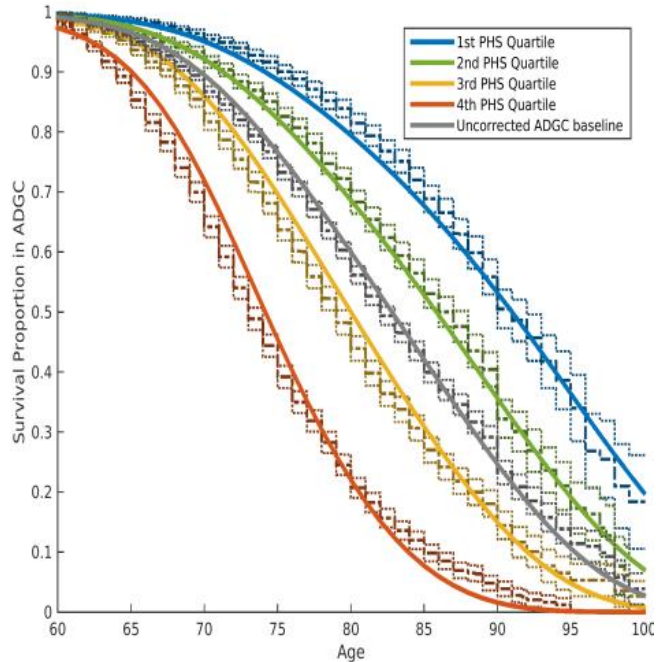


Discovery of shared genomic loci using the conditional false discovery rate approach

Review

First Online: 13 September 2019

Polygenic prediction disease onset



Age	Population Baseline*	PHS 1 percentile (95% CI)	PHS 20 th percentile (95% CI)	PHS 80 th percentile (95% CI)	PHS 99 th percentile (95% CI)	APOE ε4+ (95% CI)	APOE ε4- (95% CI)
60	0.08	0.03 (0.02,0.04)	0.05 (0.03,0.07)	0.14 (0.08, 0.21)	0.48 (0.27, 0.69)	0.19 (0.18, 0.20)	0.06 (0.06, 0.7)
65	0.17	0.05 (0.03,0.08)	0.1 (0.06, 0.15)	0.29 (0.17, 0.42)	0.97 (0.56,1.39)	0.38 (0.36, 0.40)	0.13 (0.12, 0.13)
70	0.35	0.11 (0.06,0.16)	0.21 (0.12,0.3)	0.6 (0.35, 0.85)	1.98 (1.13, 2.84)	0.78 (0.74, 0.82)	0.26 (0.25, 0.27)
75	0.71	0.22 (0.13,0.32)	0.43 (0.25,0.62)	1.22 (0.71, 1.73)	4.03 (2.3, 5.77)	1.58 (1.51, 1.66)	0.53 (0.52, 0.55)
80	1.44	0.45 (0.26,0.64)	0.88 (0.51,1.25)	2.47 (1.44, 3.51)	8.2 (4.67, 11.73)	3.22 (3.06, 3.38)	1.08 (1.05, 1.11)
85	2.92	0.92 (0.54,1.31)	1.8 (1.04, 2.55)	5.03 (2.92, 7.15)	16.68 (9.5, 23.86)	6.55 (6.23, 6.87)	2.2 (2.13, 2.27)
90	5.95	1.88 (1.09,2.66)	3.65 (2.12, 5.18)	10.24 (5.94, 14.53)	33.93 (19.33, 48.54)	13.33 (12.68, 13.98)	4.48 (4.34, 4.61)
95	12.1	3.82 (2.22,5.42)	7.43 (4.32, 10.54)	20.82 (12.09, 29.56)	69.02 (39.32, 98.72)	27.11 (25.79, 28.43)	9.1 (8.83, 9.38)



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Thank you

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