

History of Biometrical Genetics: Causes of Individual Differences

Abdel Abdellaoui

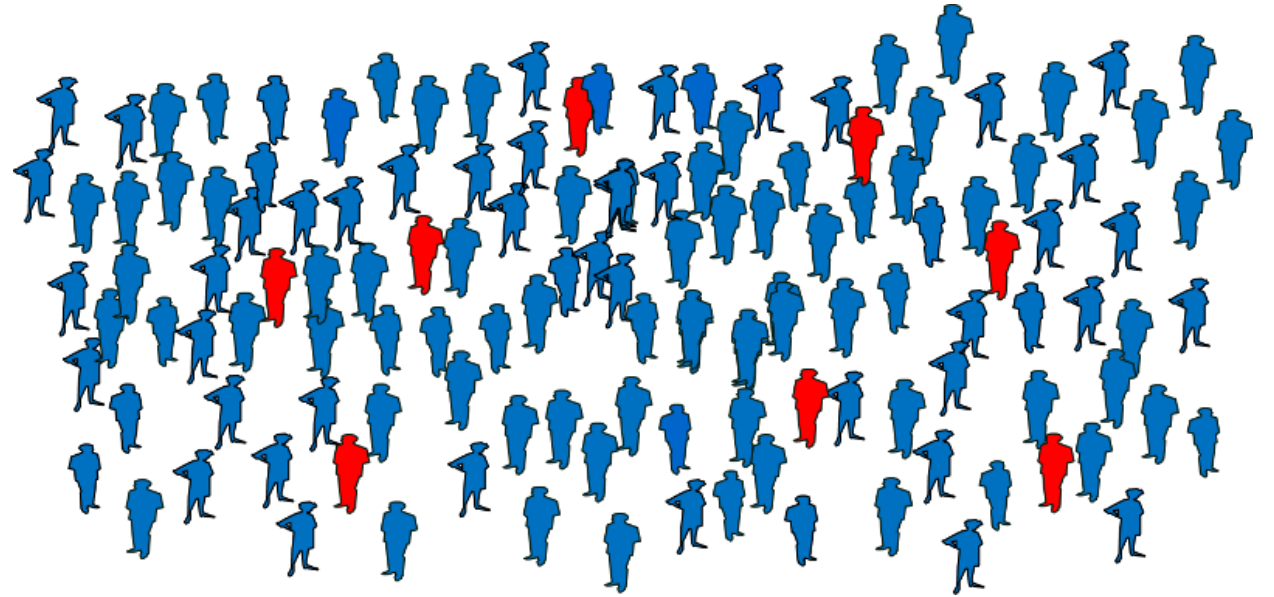


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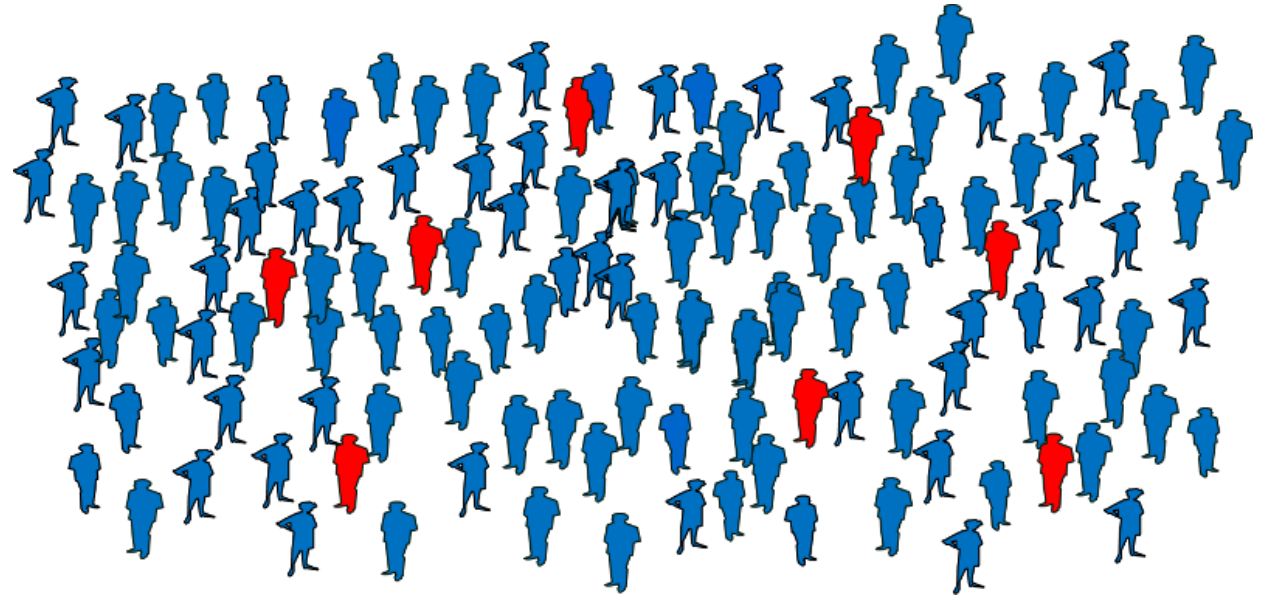


a.abdellaoui@amsterdamumc.nl

Where do differences between individuals come from?



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International Journal of Epidemiology 2001;**30**:427–432

REITERATION

Sick individuals and sick populations

Geoffrey Rose

Where do differences between individuals come from?

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REITERATION

Sick individuals and sick populations

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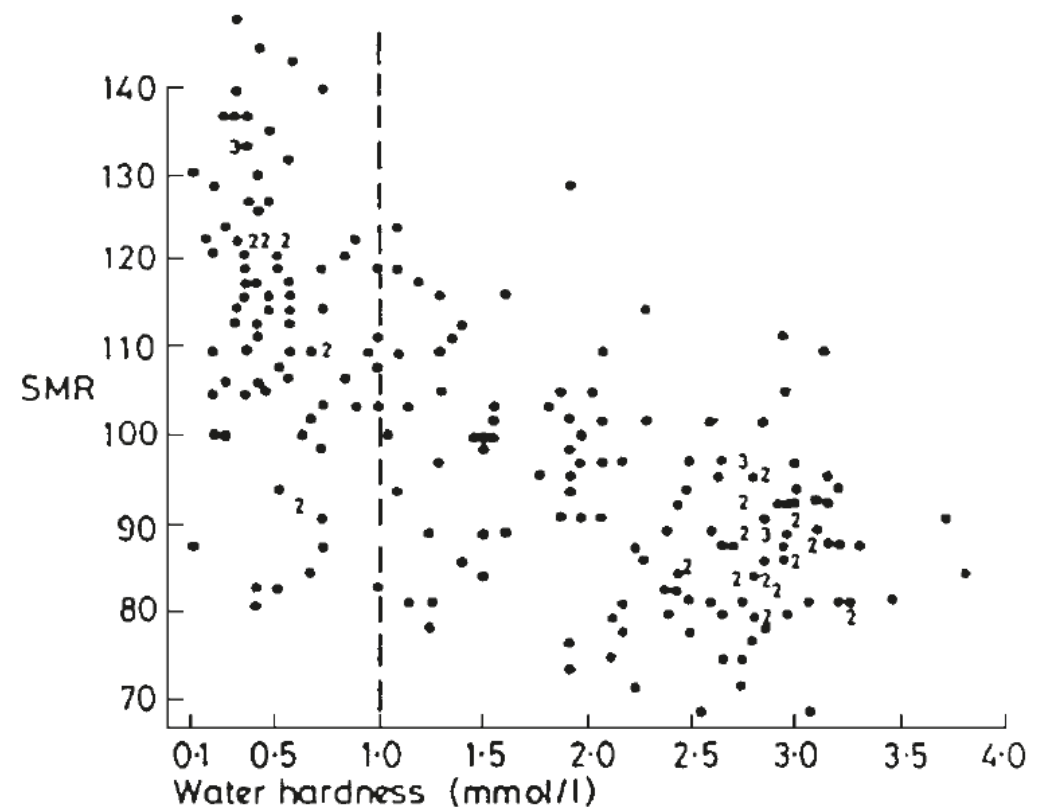


Figure 1 Relation between water quality and cardiovascular mortality in towns of the UK¹

Where do differences between individuals come from?

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International Journal of Epidemiology 2001;30:427-432

REITERATION

Sick individuals and sick populations

Geoffrey Rose

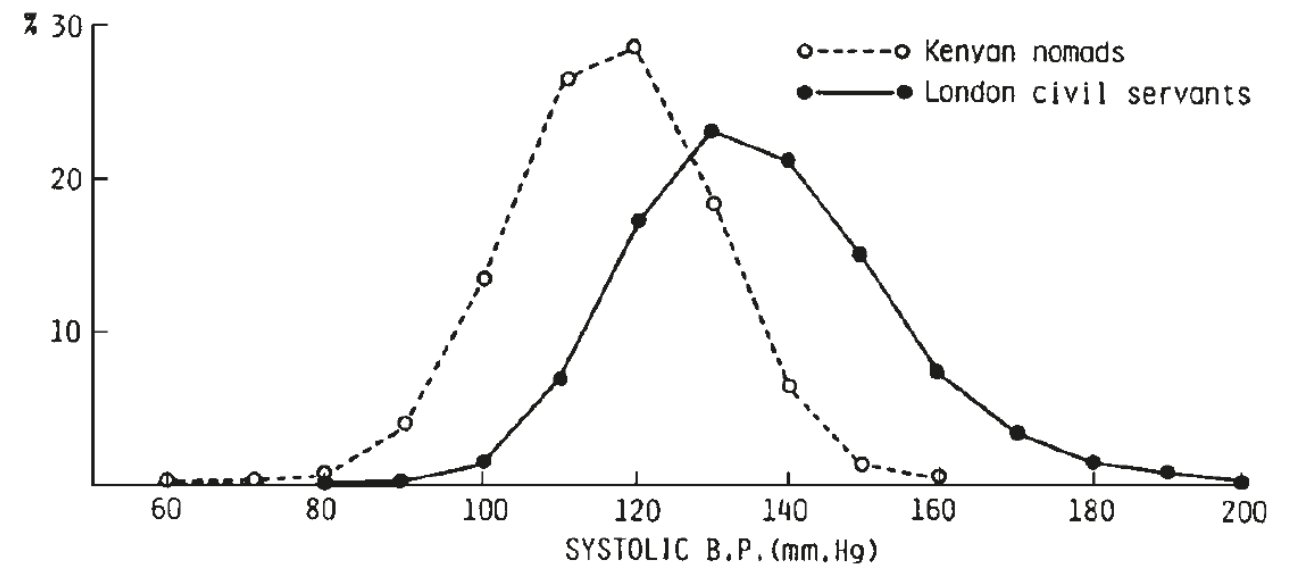
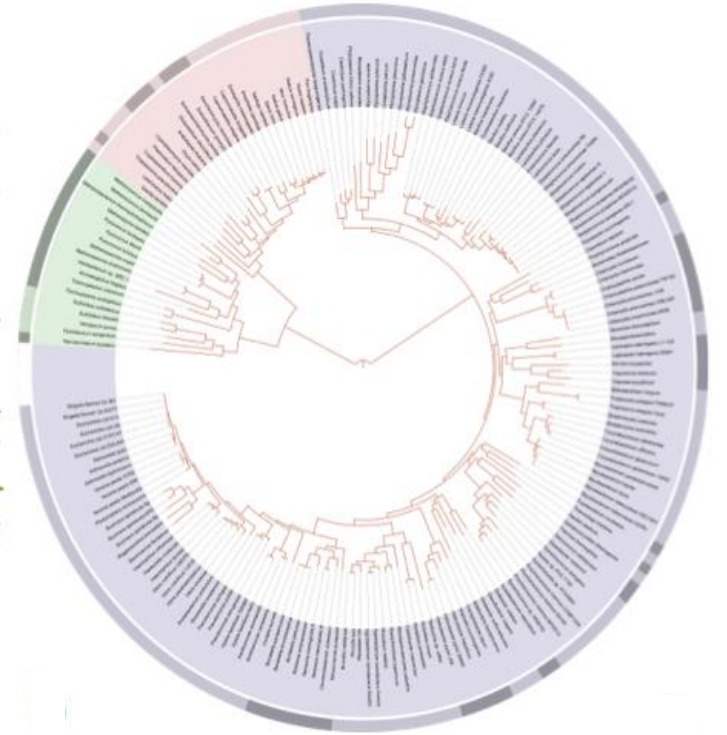
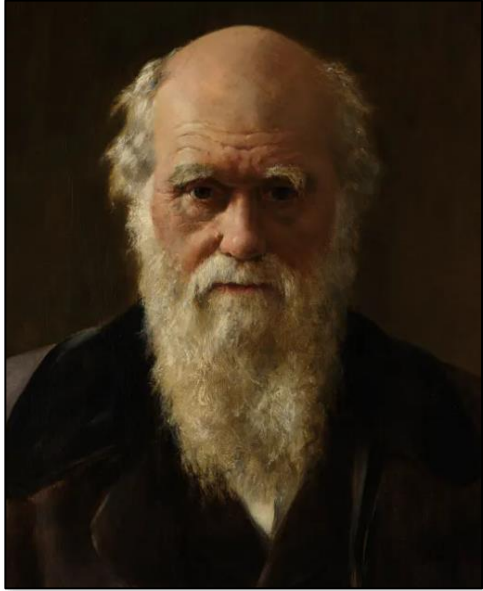
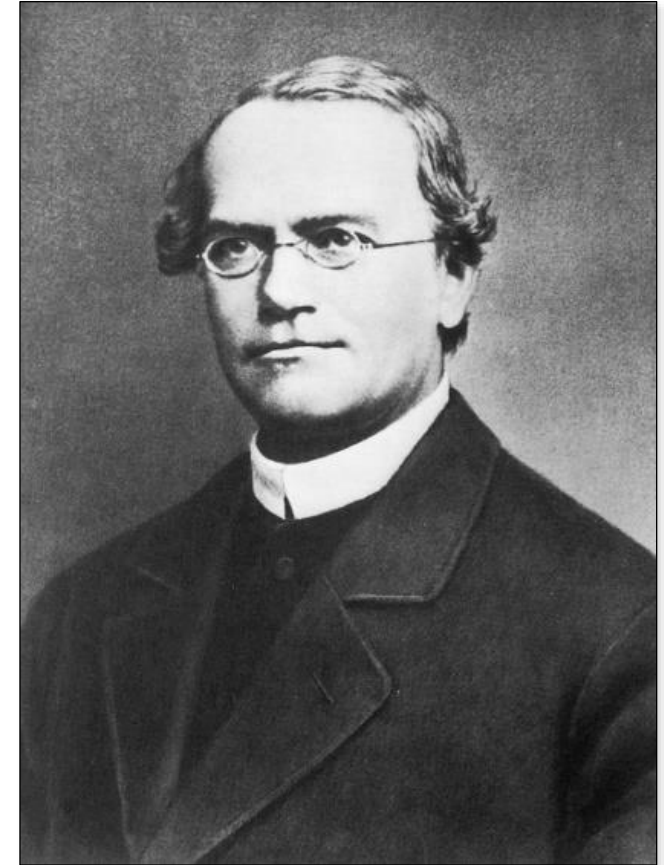
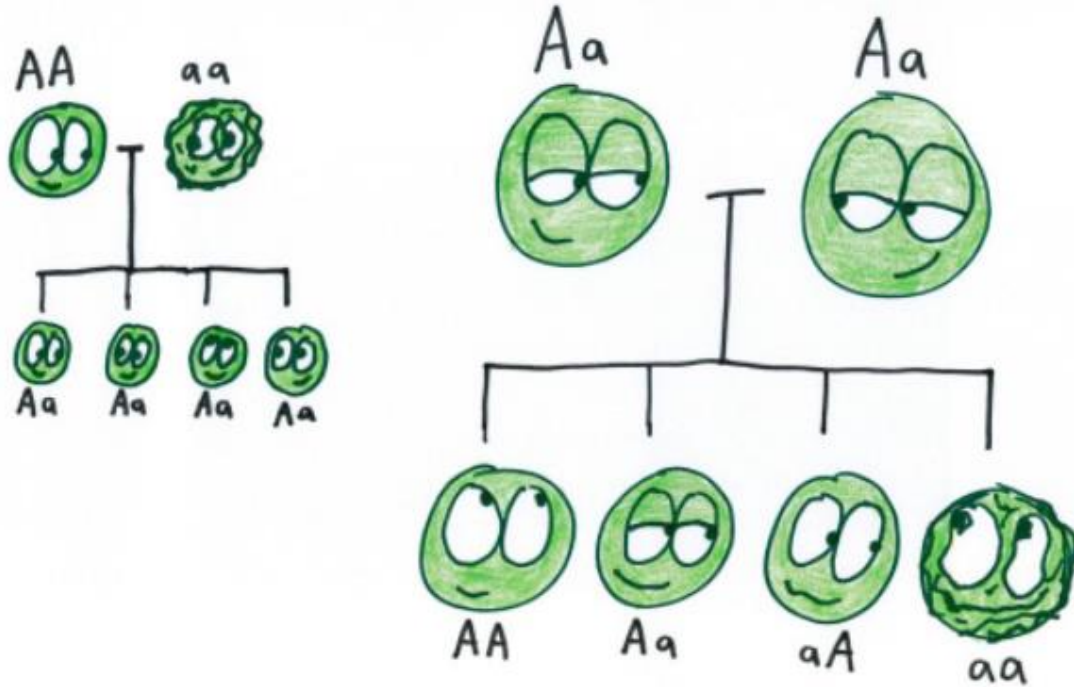


Figure 2 Distributions of systolic blood pressure in middle-aged men in two populations^{2,3}

On the Origin of Species (Darwin, 1859)

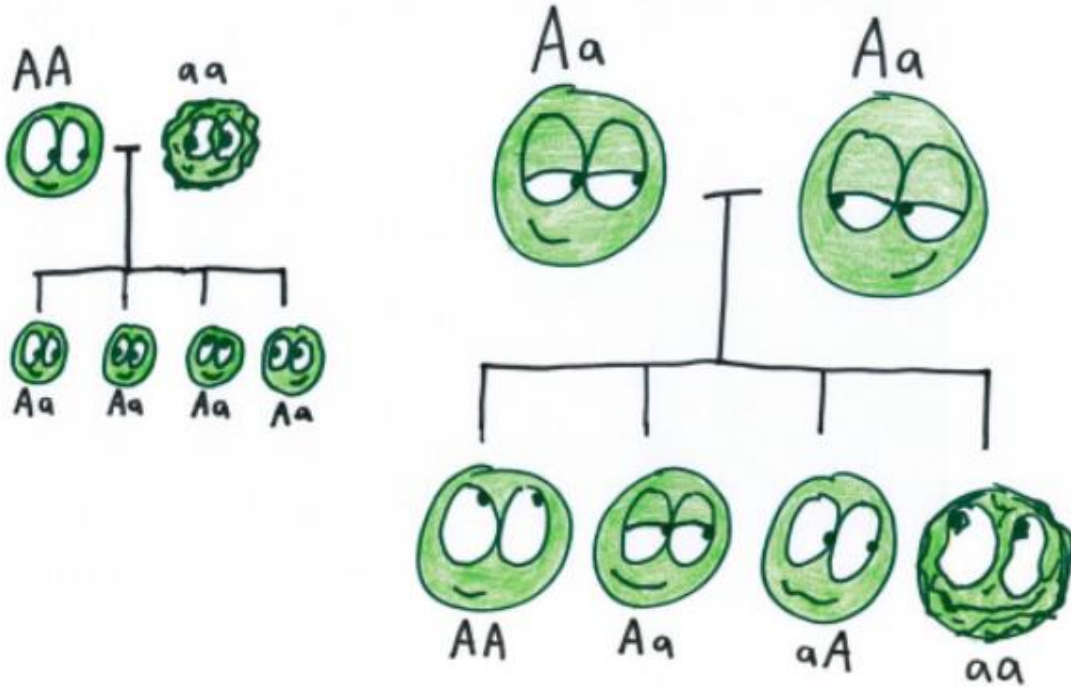


Laws of Mendel



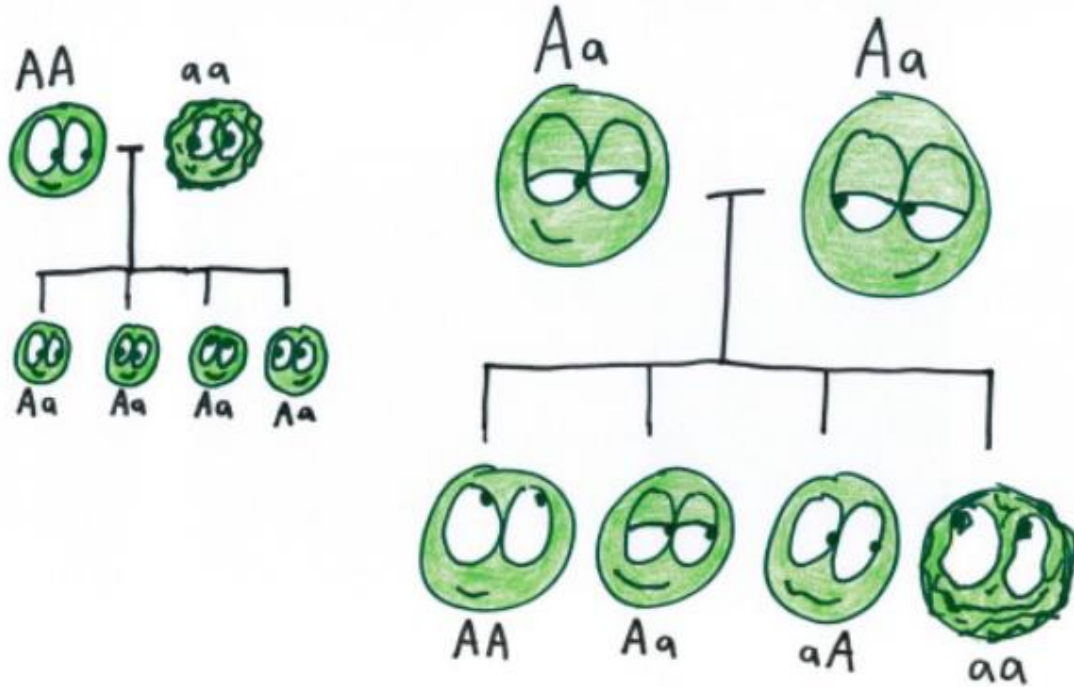
Laws of Mendel

- Law of segregation:
 - One out of two alleles is passed down by each parent

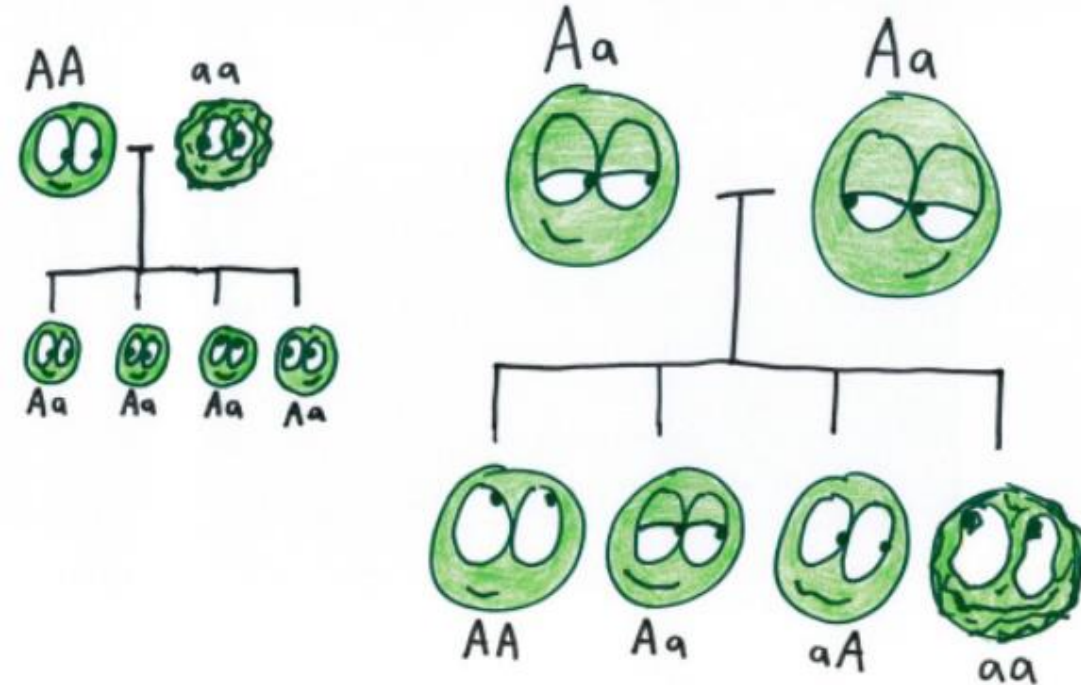


Laws of Mendel

- Law of segregation:
 - One out of two alleles is passed down by each parent
- Law of dominance:
 - Some alleles are dominant or recessive. An organism with at least one dominant allele will display the effect of the dominant allele



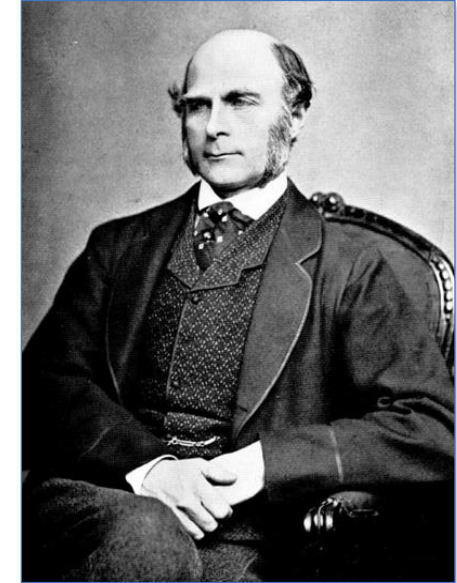
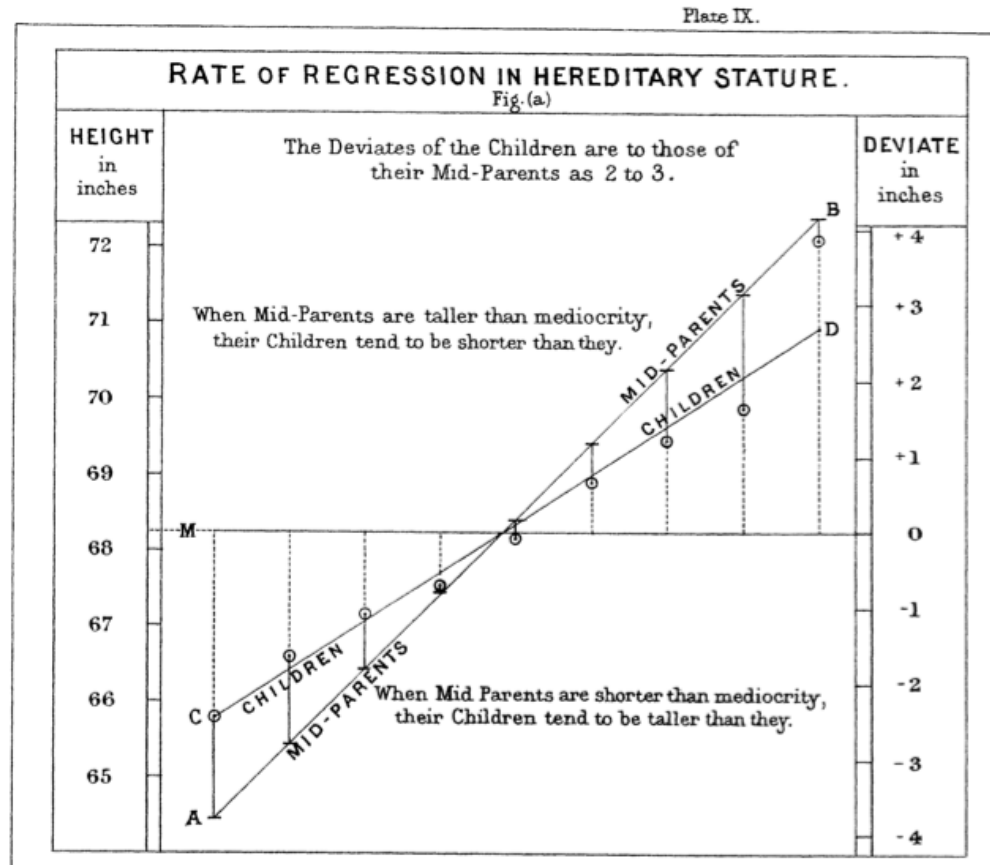
Laws of Mendel



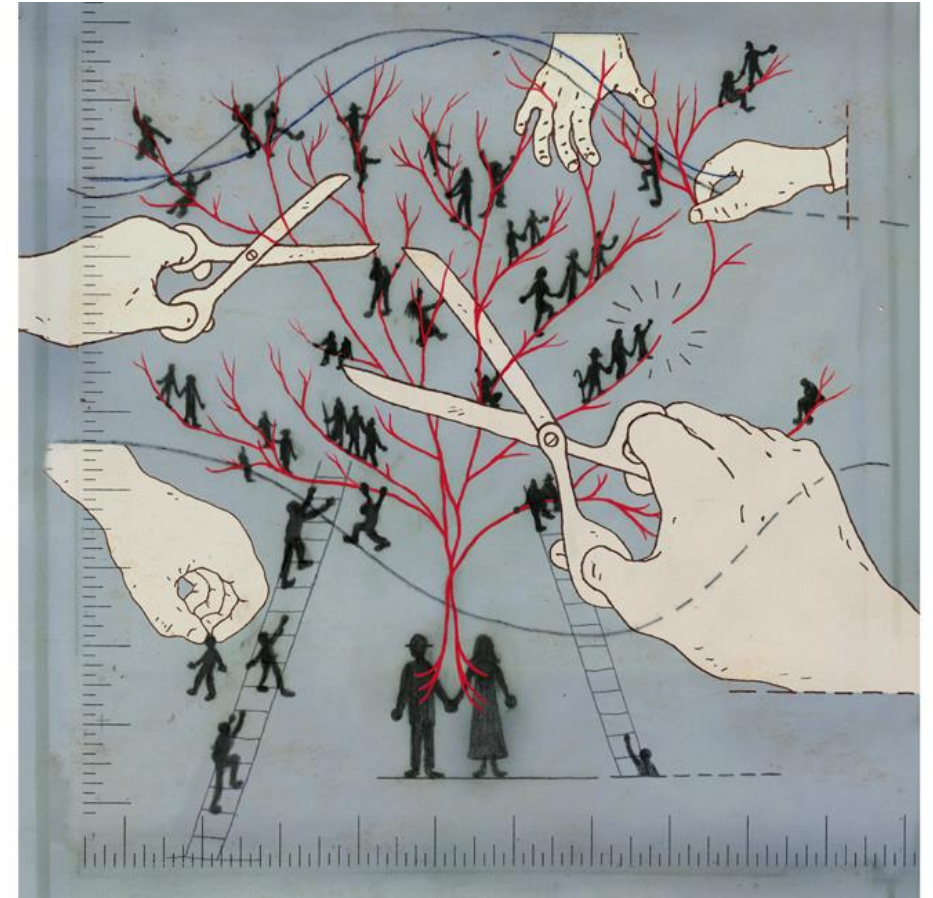
- Law of segregation:
 - One out of two alleles is passed down by each parent
- Law of dominance:
 - Some alleles are dominant or recessive. An organism with at least one dominant allele will display the effect of the dominant allele
- Law of independent assortment:
 - Genes for different traits are passed down independently from each other



Regression toward mediocrity in hereditary stature (Galton 1886)



Galton also invented **Eugenics**:
Improving the “genetic quality” of the
population through selective parenthood.



ON THE LAWS OF INHERITANCE IN MAN*.

I. INHERITANCE OF PHYSICAL CHARACTERS.

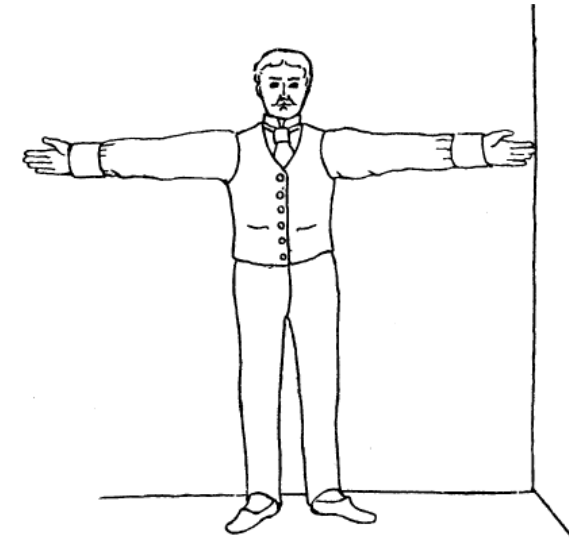
By KARL PEARSON, F.R.S., assisted by ALICE LEE, D.Sc.

University College, London.

FAMILY MEASUREMENTS.

Professor KARL PEARSON, of University College, London, would esteem it a great favour if any persons in a position to do so, would assist him by making one set (or if possible several sets) of anthropometric measurements on their own family, or on families with whom they are acquainted. The measurements are to be made use of for testing theories of heredity, no names, except that of the recorder, are required, but the Professor trusts to the *bona fides* of each recorder to send only correct results.

Each family should consist of a father, mother, and at least one son or daughter, not necessarily the eldest. The sons or daughters are to be at least 18 years of age, and measurements are to be made on not more than two sons and two daughters of the same family. If more than two sons or two daughters are easily accessible, then not the tallest but the eldest of those accessible should be selected.



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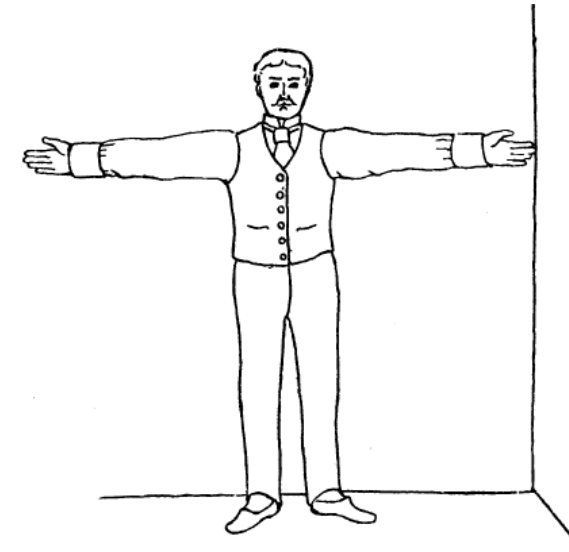
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I. *Family Record Series.* About 1893 I drew up in conjunction with my then colleague, W. F. R. Weldon, the directions for family measurement which are described below. The measurements were in great part carried out by college students*, and I largely owe the success of this series to the energy and time devoted to the collection of the data by Dr Alice Lee. In the course of four to five years about 1100 cards were filled in. The tabling of the data on these cards and the calculation of the statistical constants, some 78 tables in all, are due entirely to Dr Lee, and occupied her spare time for nearly two years.



RA Fisher (1918). Transactions of the Royal Society of Edinburgh 52: 399-433

XV.—The Correlation between Relatives on the Supposition of Mendelian Inheritance. By R. A. Fisher, B.A. Communicated by Professor J. ARTHUR THOMSON. (With Four Figures in Text.)

(MS. received June 15, 1918. Read July 8, 1918. Issued separately October 1, 1918.)

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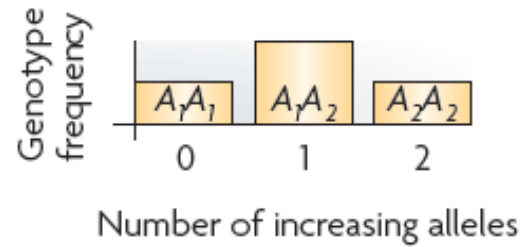
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GENETICS | PERSPECTIVES
From R.A. Fisher’s 1918 Paper to GWAS a Century Later

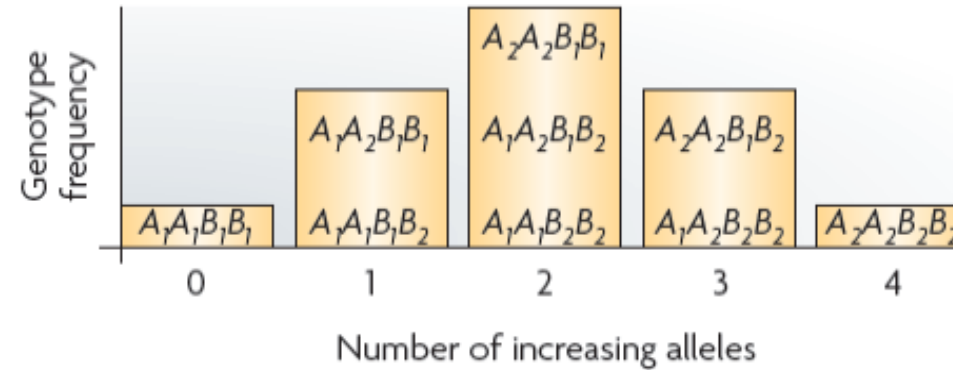
Peter M. Visscher*† and Michael E. Goddard*§



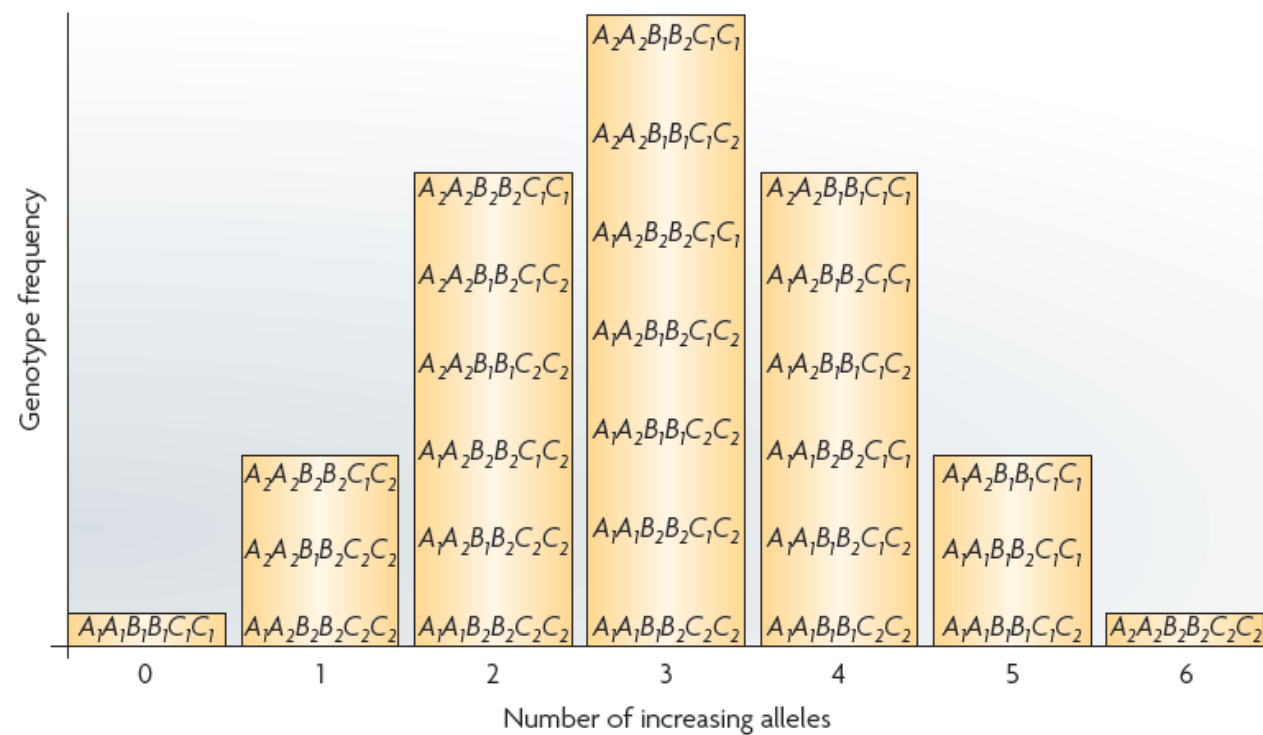
Ronald Fisher reconciles Mendel's laws & quantitative traits



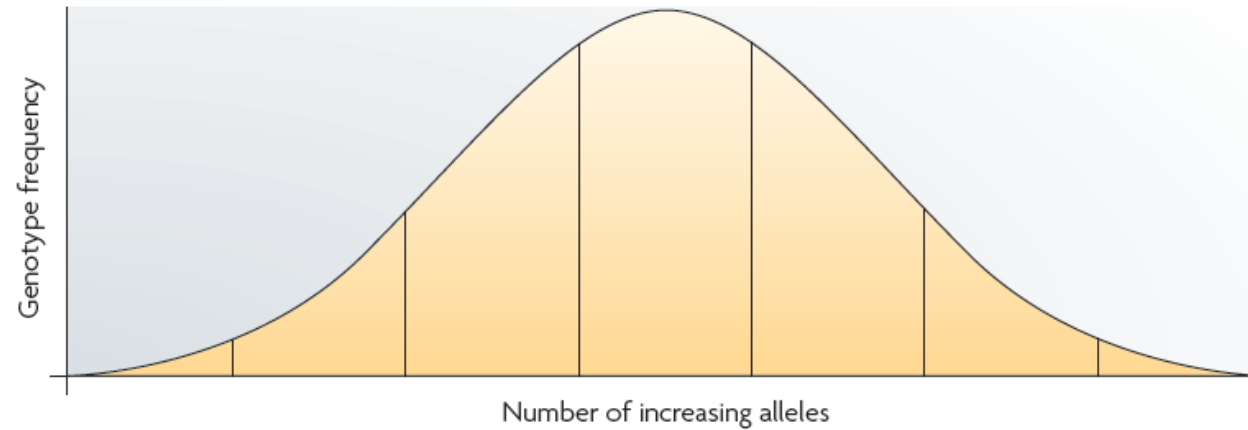
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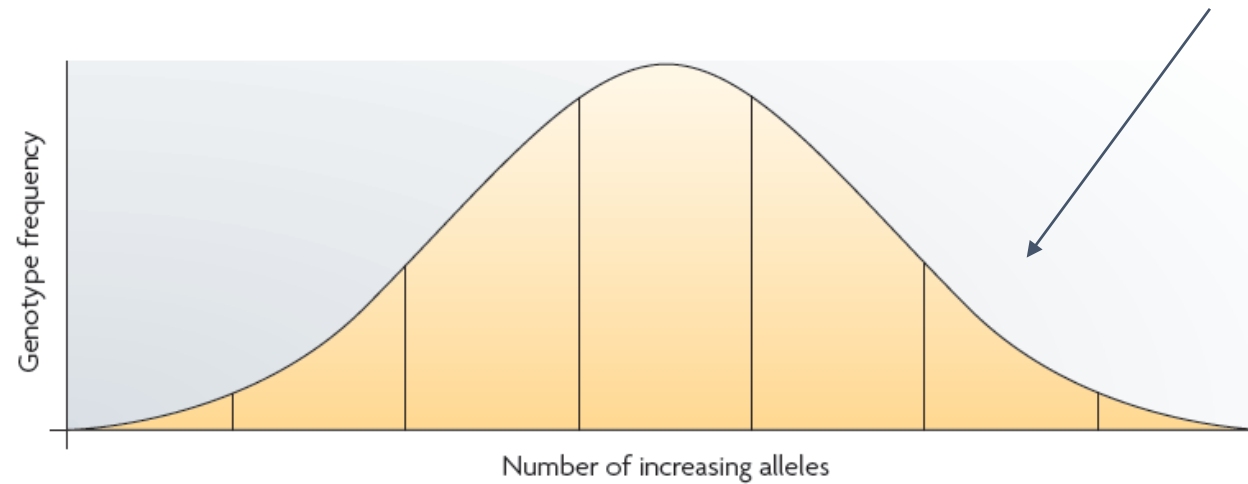


Ronald Fisher reconciles Mendel's laws & quantitative traits



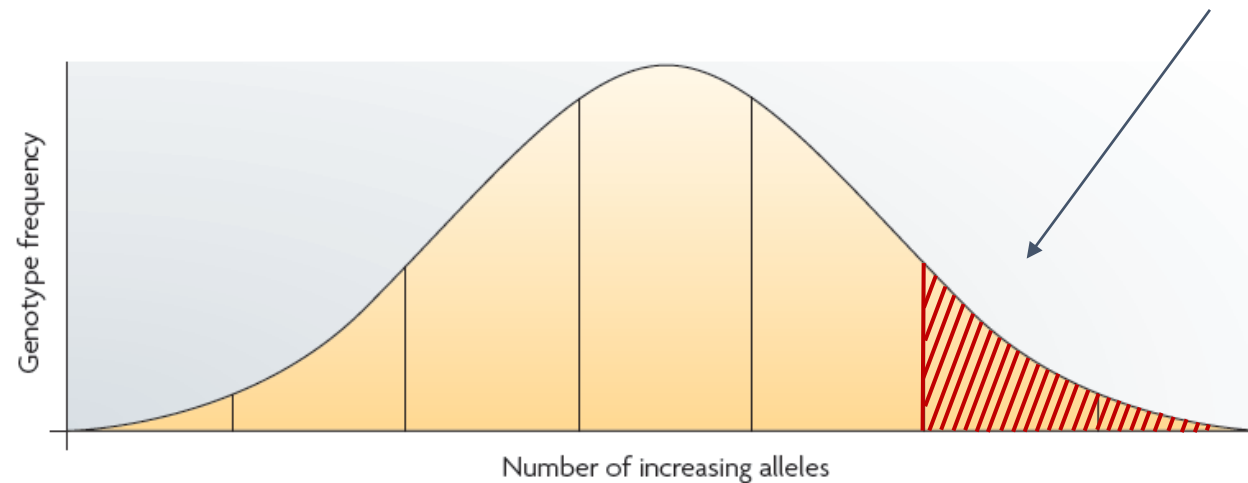
Ronald Fisher reconciles Mendel's laws & quantitative traits

**Complex trait =
many genes + environment**



Ronald Fisher reconciles Mendel's laws & quantitative traits

Complex **disease** =
many genes + environment

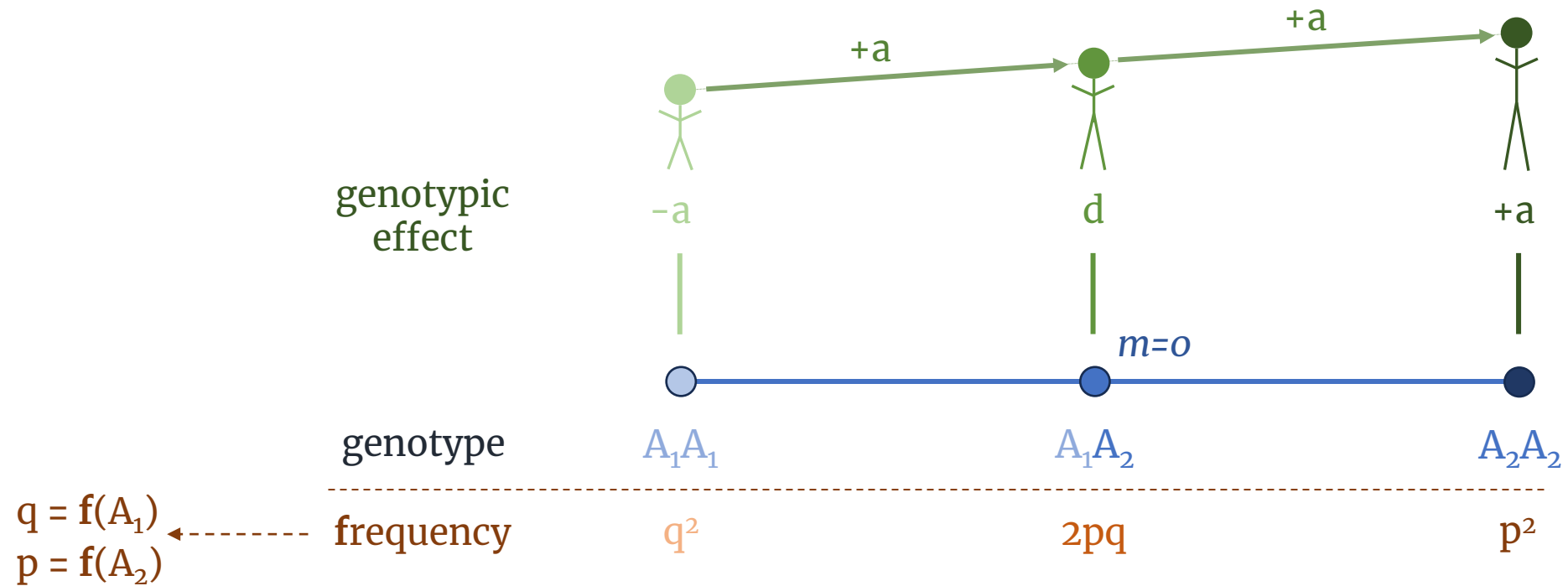


Liability threshold model



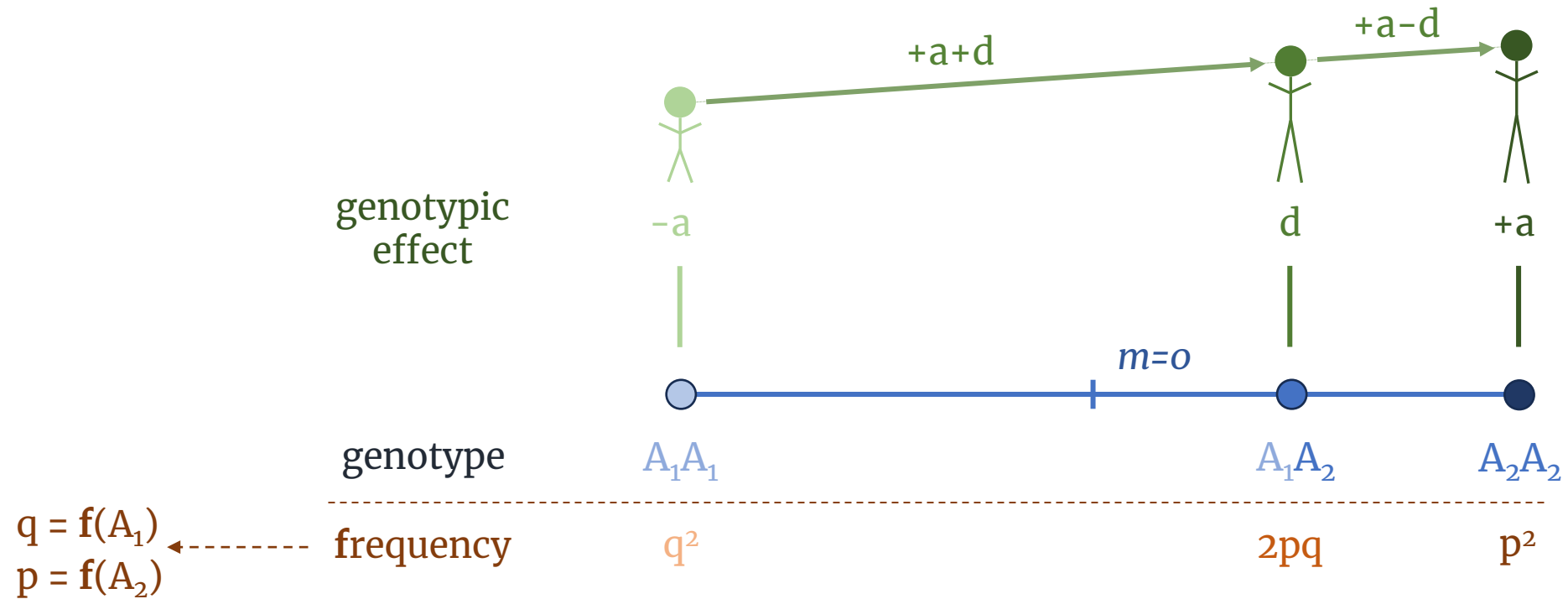
biometrical model

genotype with an additive effect ($d=0$)



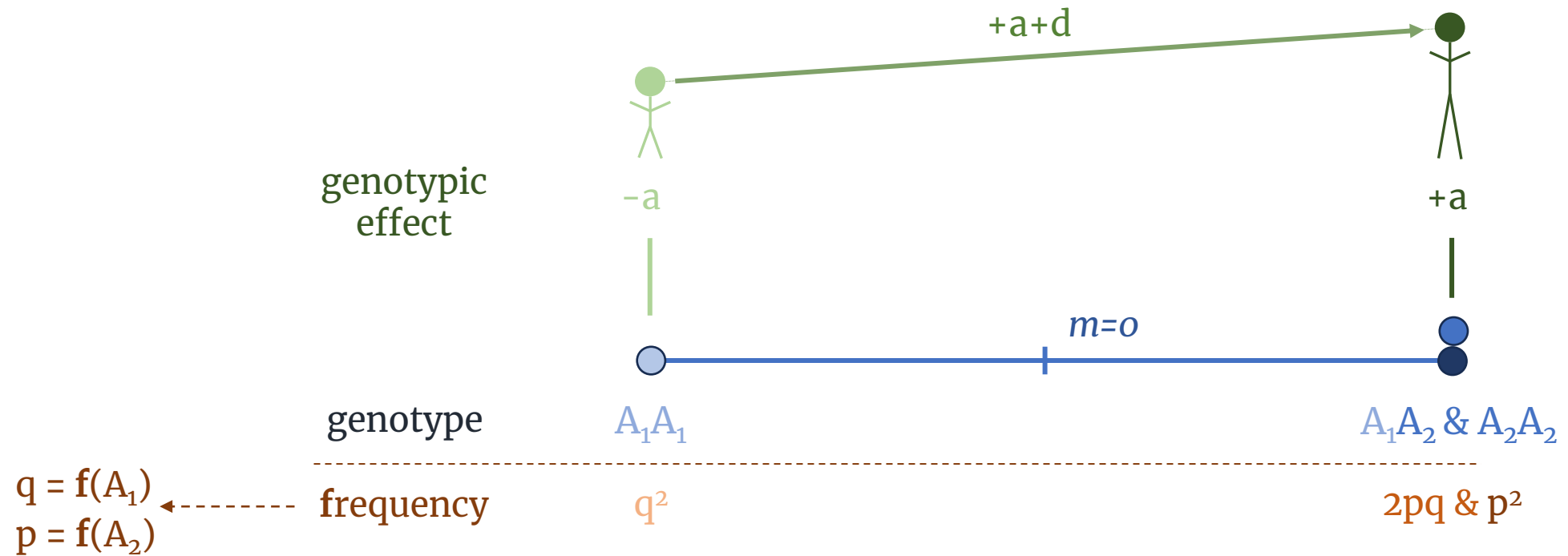
biometrical model

genotype with an additive and dominance effect ($d > 0$)

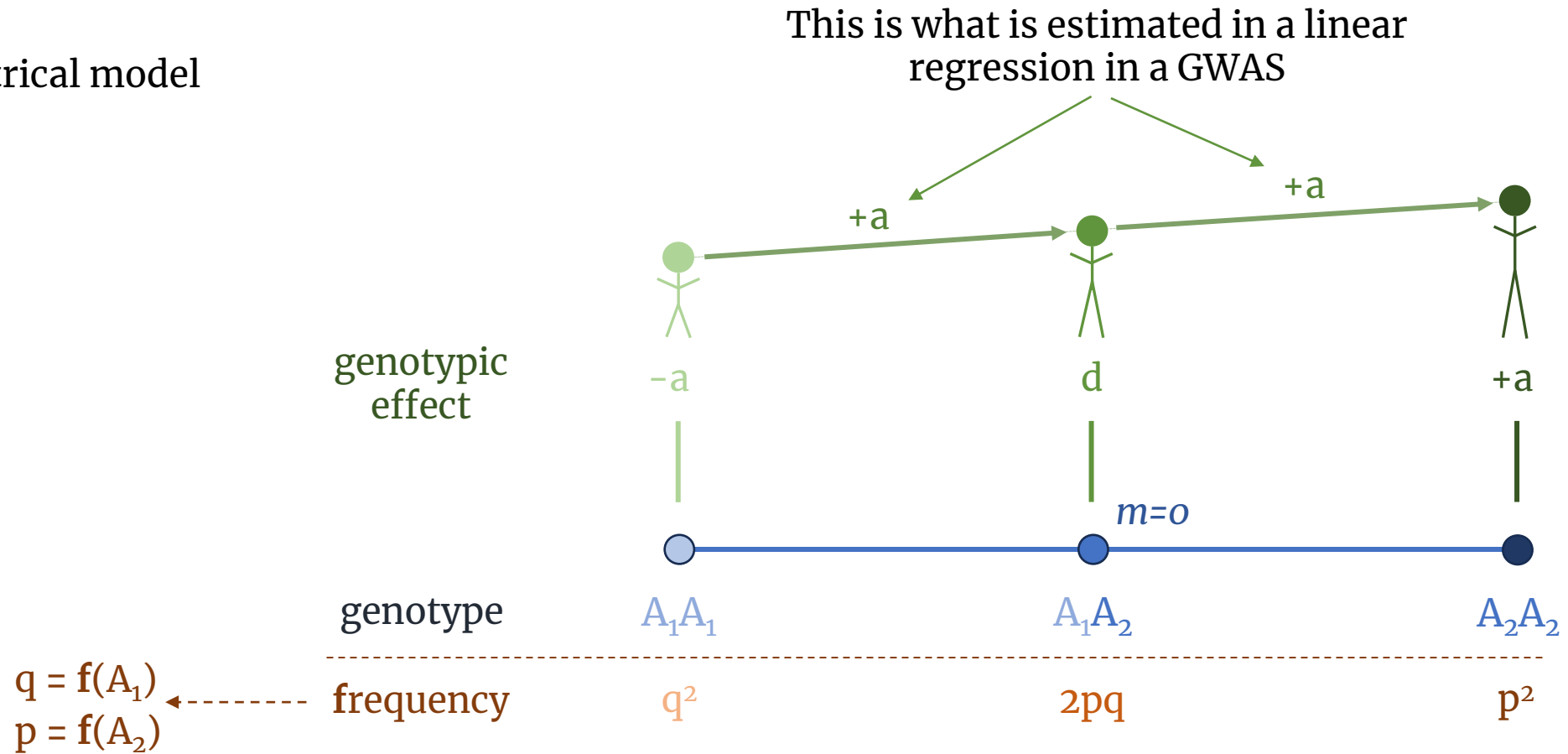


biometrical model

genotype with a complete dominance effect ($d=a$)



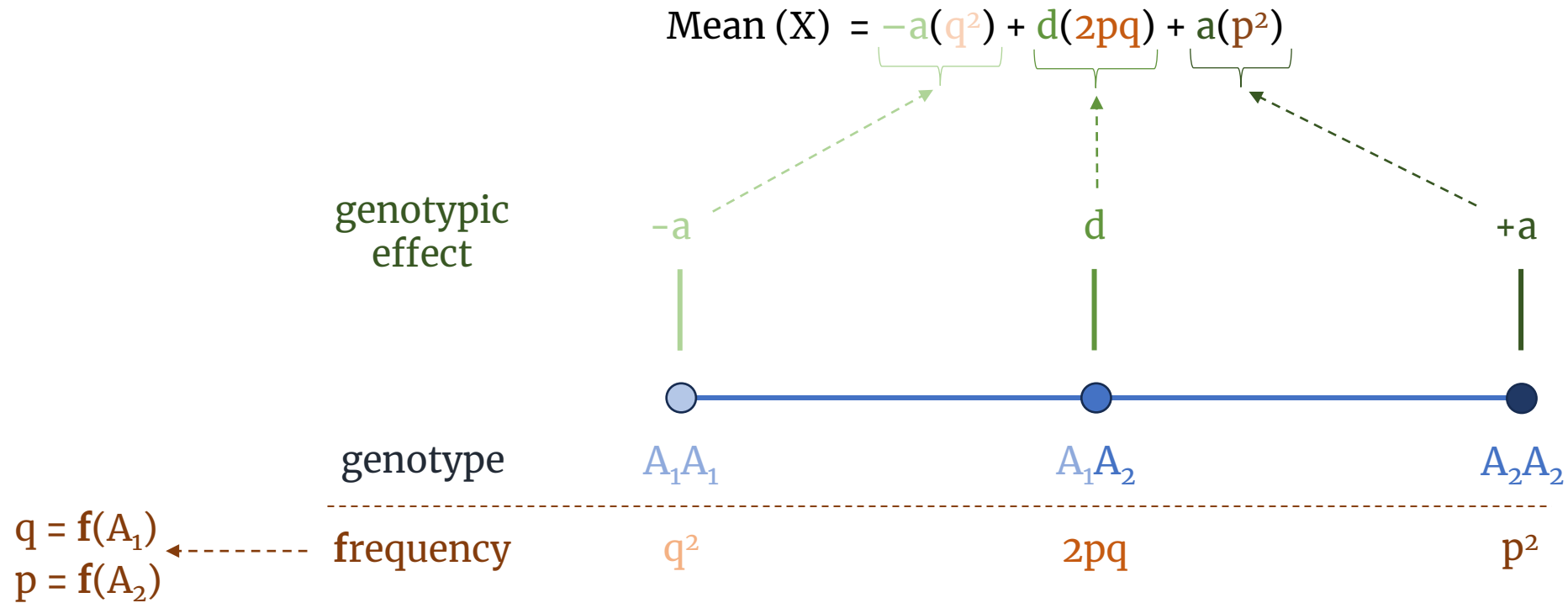
biometrical model



biometrical model

contribution of the locus to the Mean (X) →

$$\mu = \sum_i x_i f(x_i)$$

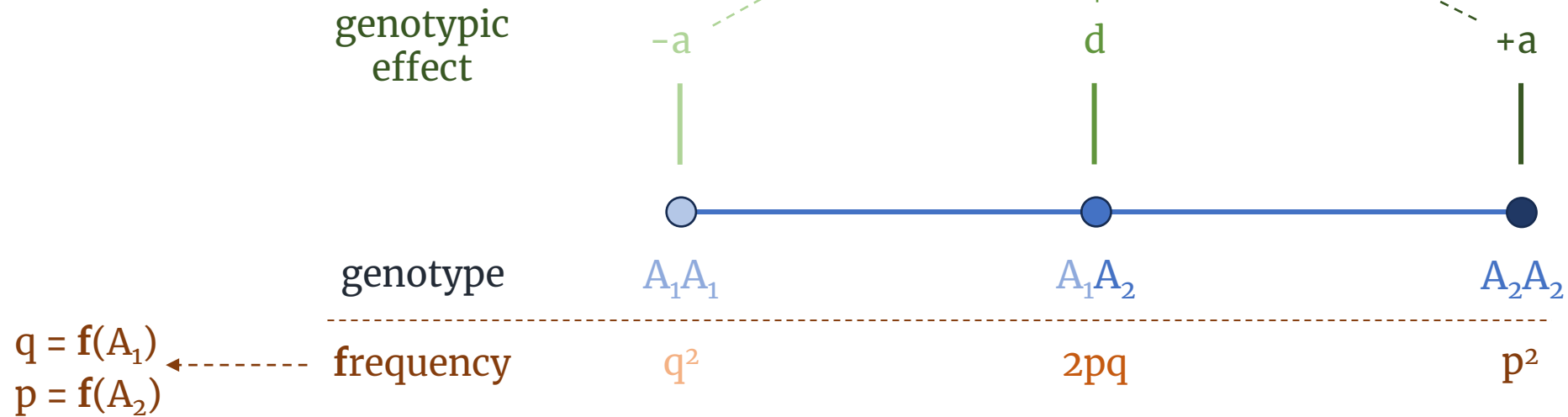


biometrical model

contribution of the locus to the Mean (X) →

$$\mu = \sum_i x_i f(x_i)$$

$$\text{Mean (X)} = -a(q^2) + d(2pq) + a(p^2) = a(p-q) + 2pqd$$

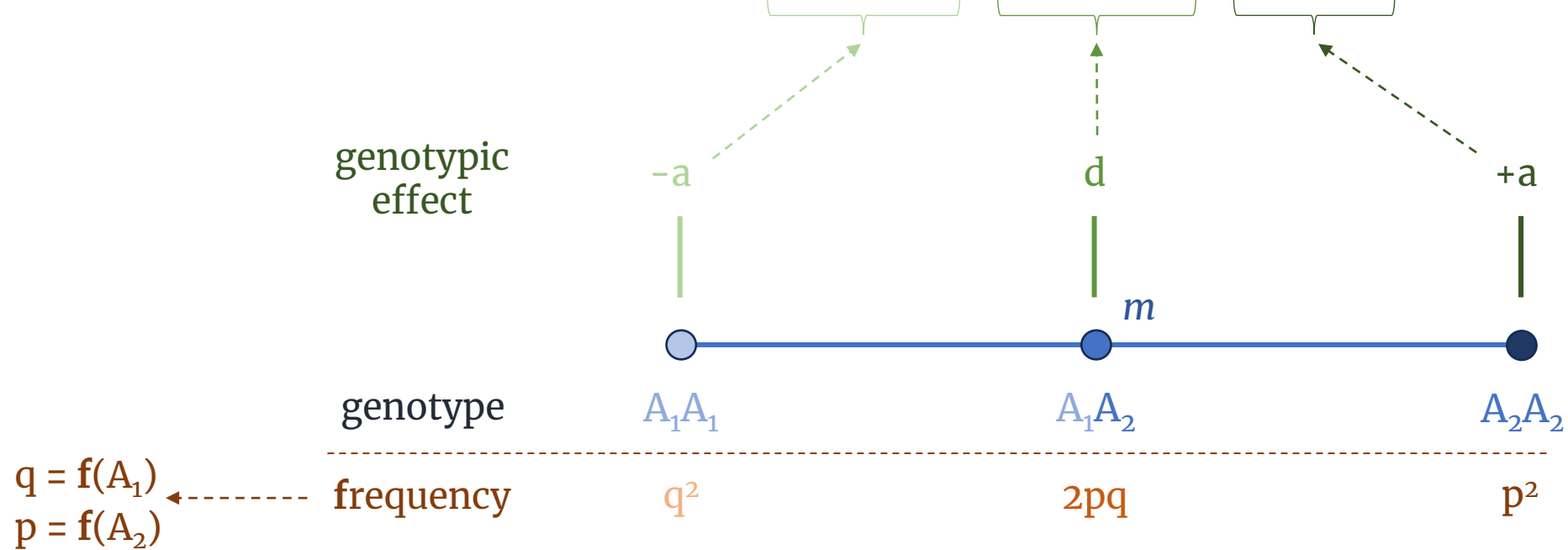


biometrical model

contribution of the locus to the Variance (X) →

$$Var = \sum_i (x_i - \mu)^2 f(x_i)$$

$$\text{Variance (X)} = (-a - m)^2 q^2 + (d - m)^2 2pq + (a - m)^2 p^2 = V_{QTL}$$



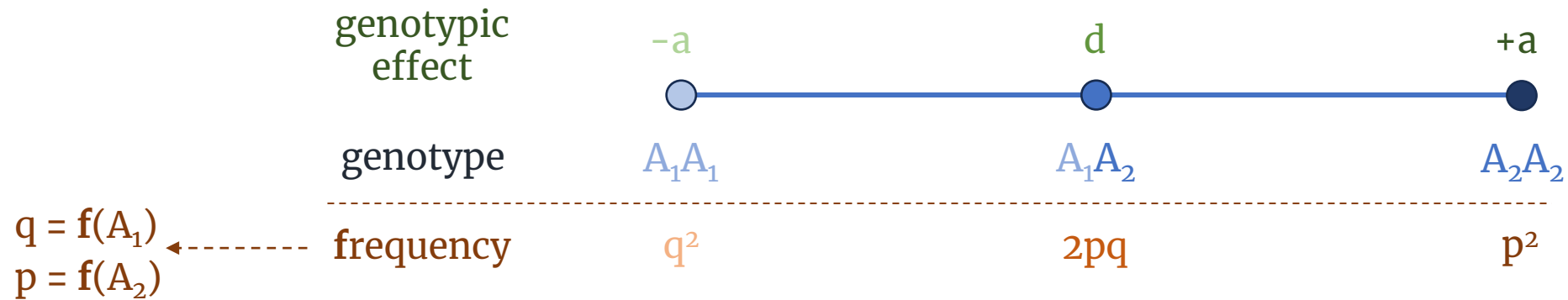
biometrical model

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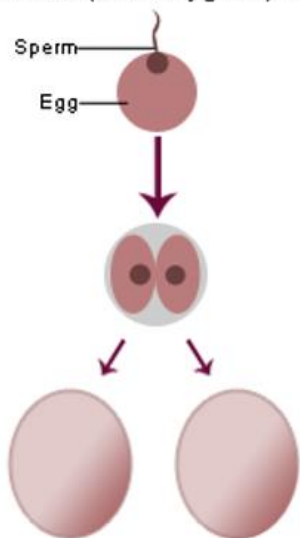
$$= \underbrace{2pq[a + (q - p)d]^2}_{V_{A_{QTL}}} + \underbrace{(2pqd)^2}_{V_{D_{QTL}}}$$



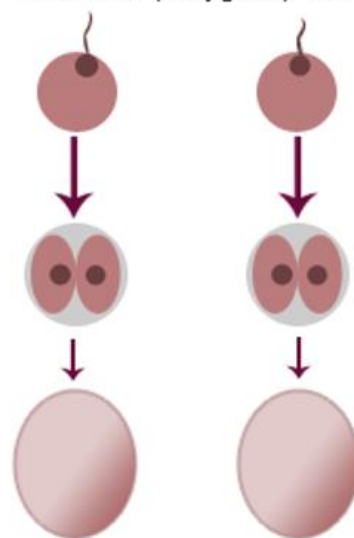
First classical twin studies (monozygotic [MZ] vs dizygotic [DZ] twins) were done in the late 1920s on intelligence.

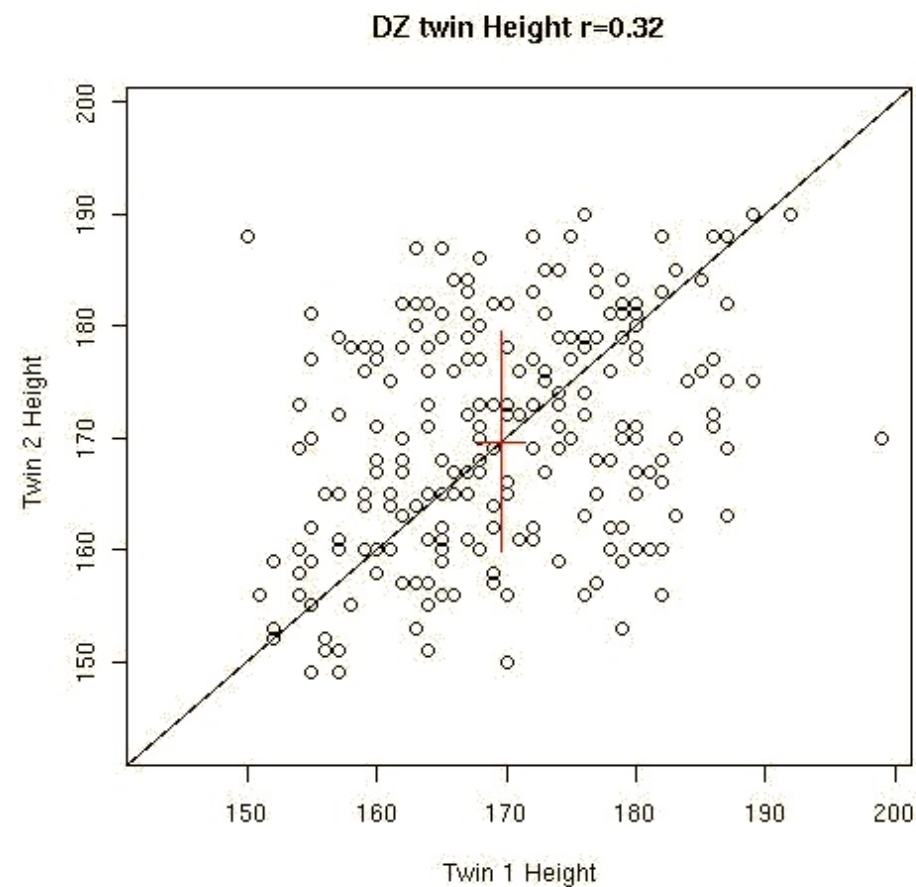
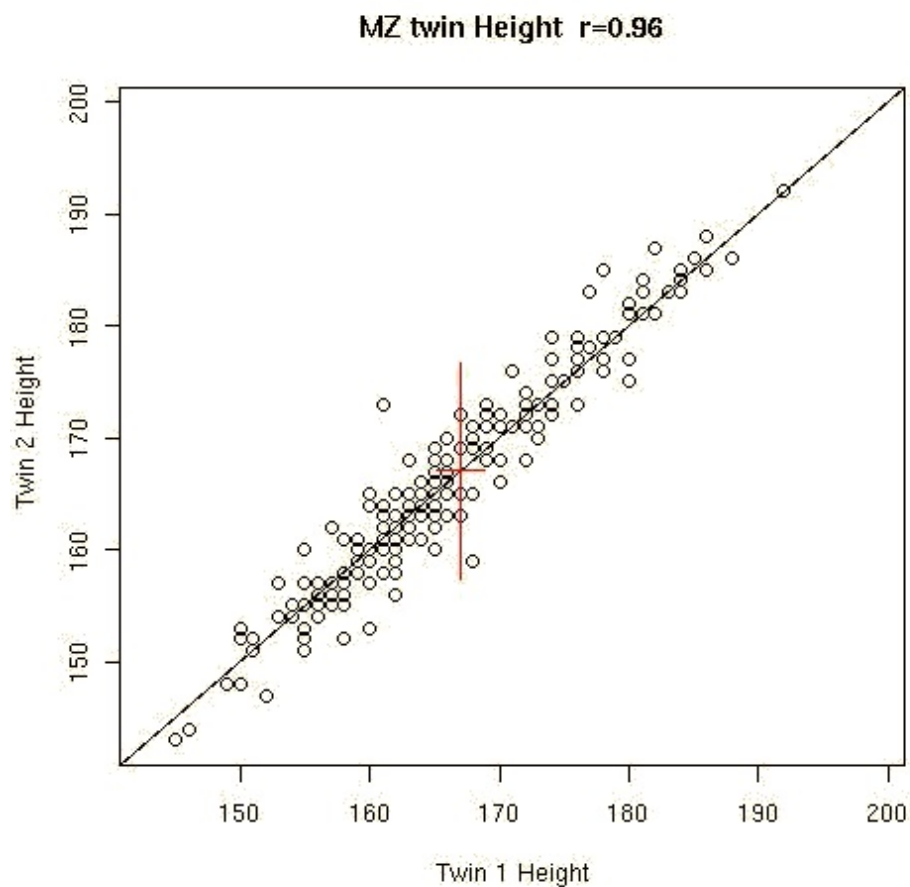


Identical (Monozygotic) Twins

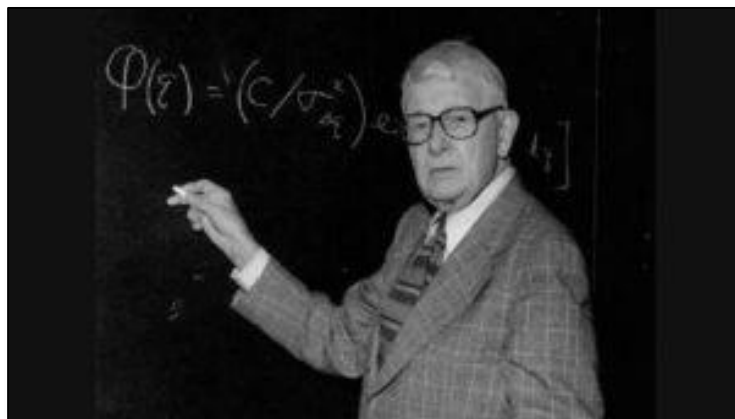


Fraternal (Dizygotic) Twins





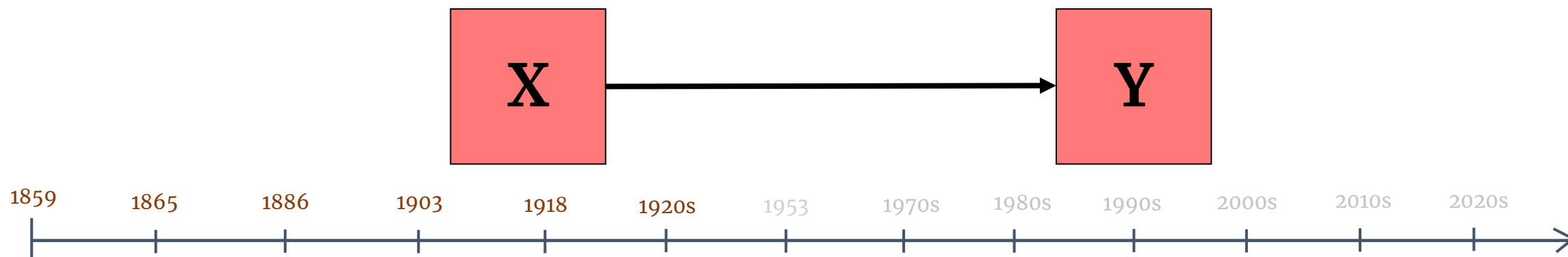
Structural Equation Modeling, 1921, Sewall Wright



Structural Equation Modeling, 1921, Sewall Wright

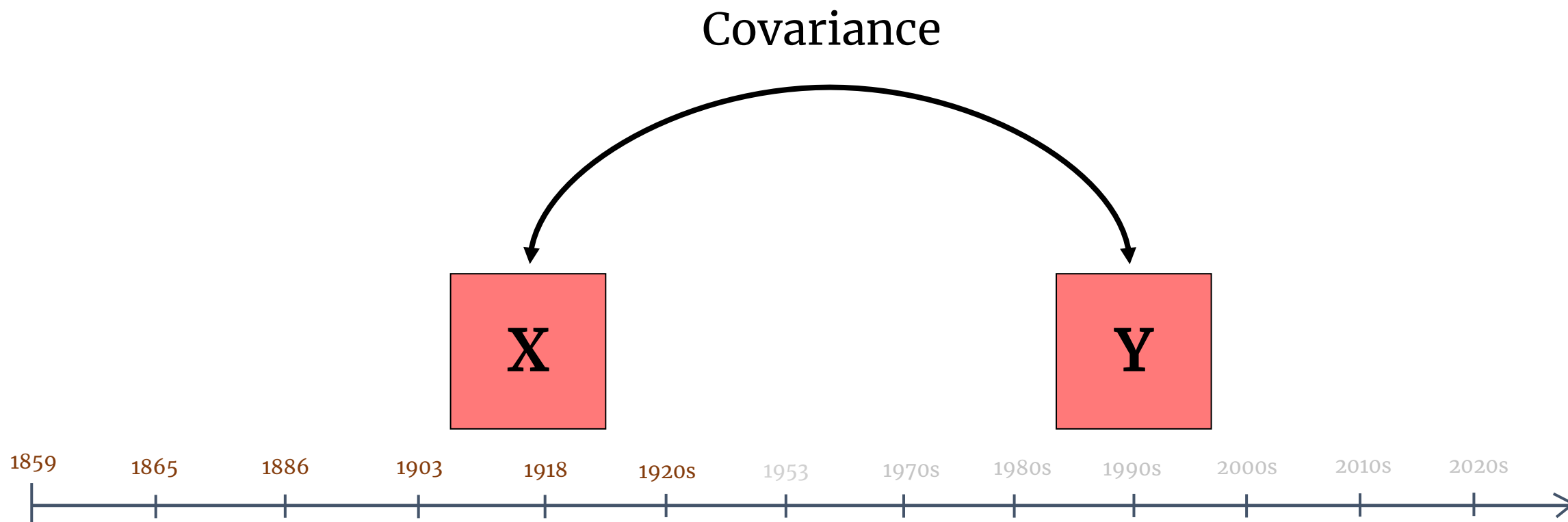
Types of relationships:

Linear Regression (“X causes Y”)



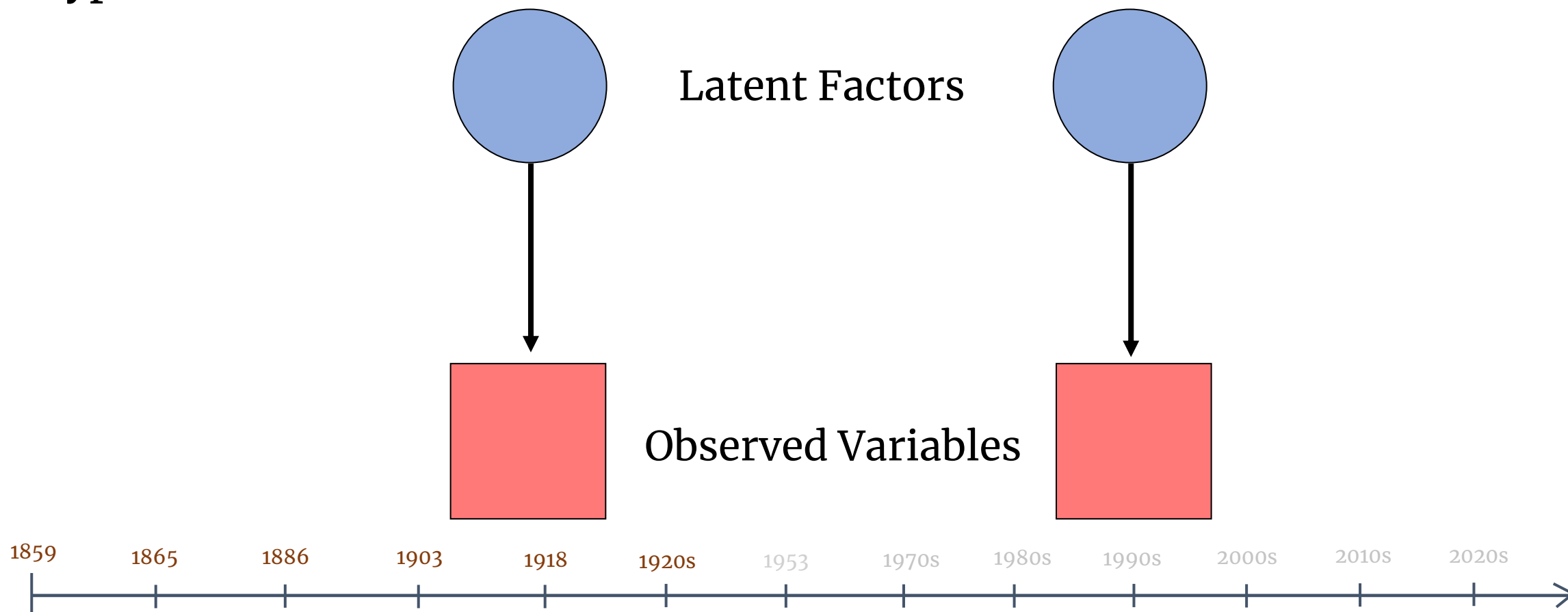
Structural Equation Modeling, 1921, Sewall Wright

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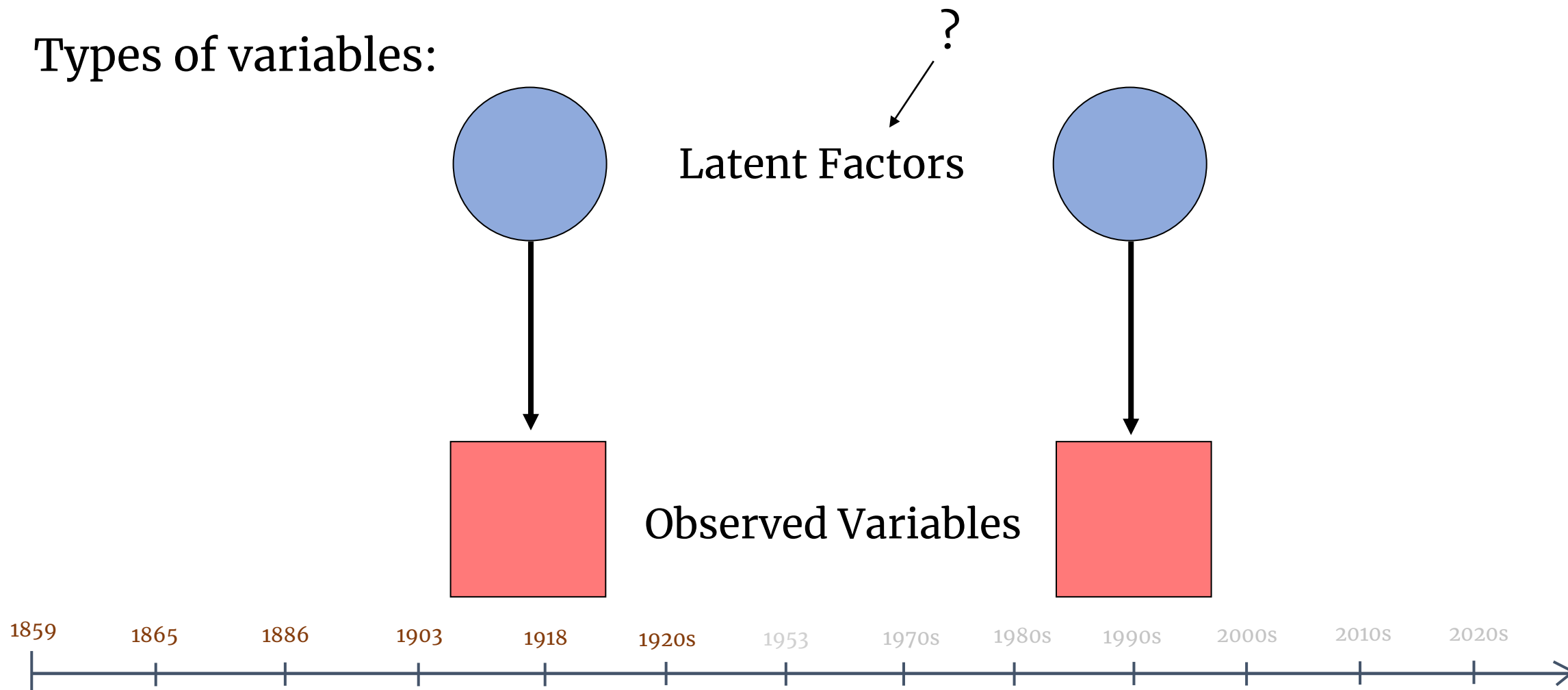
Structural Equation Modeling, 1921, Sewall Wright

Types of variables:



Structural Equation Modeling, 1921, Sewall Wright

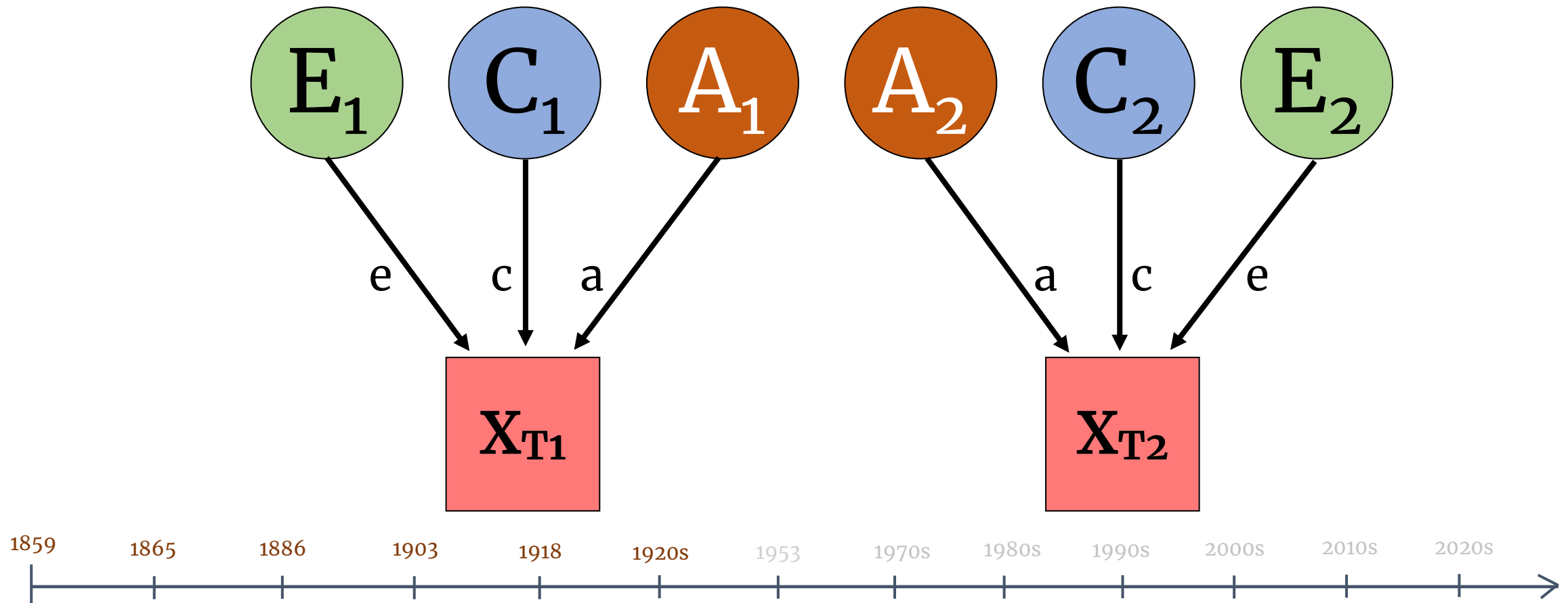
Types of variables:

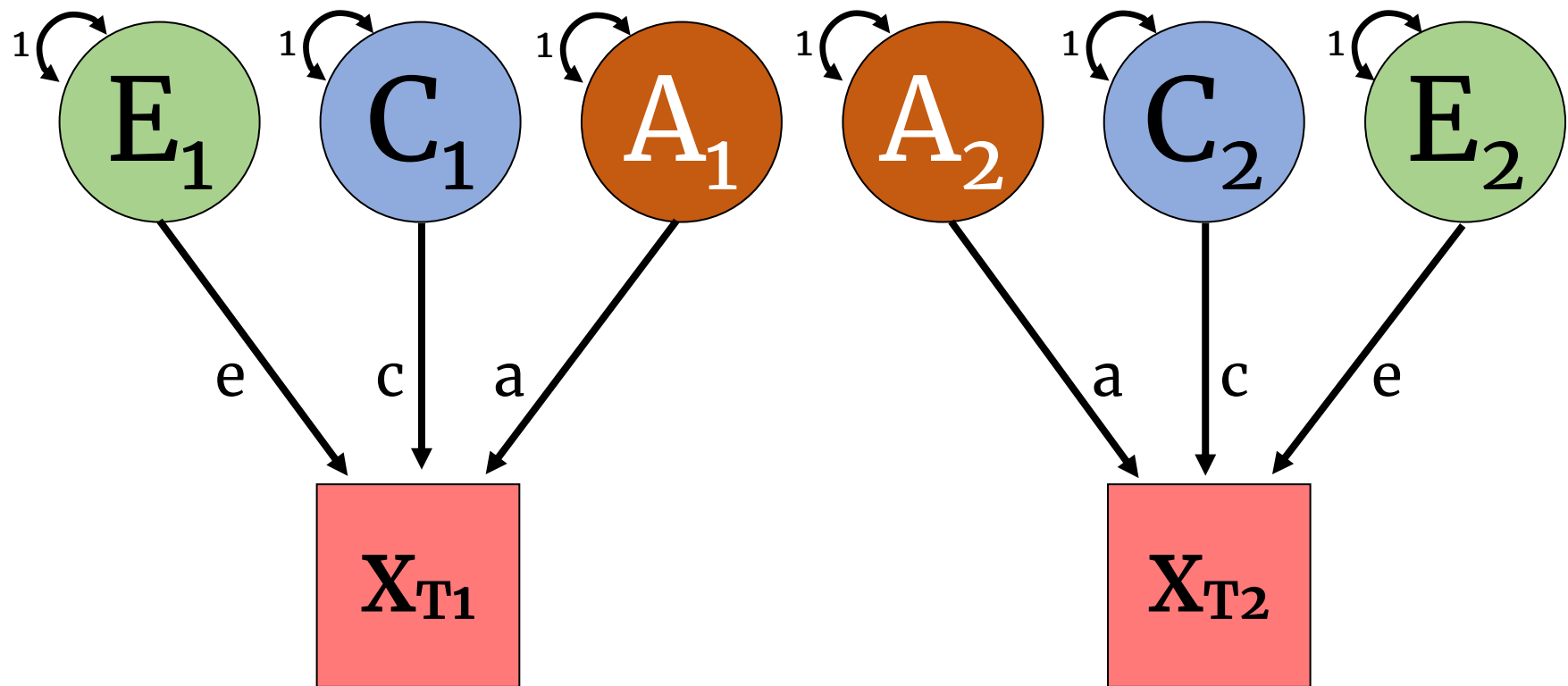


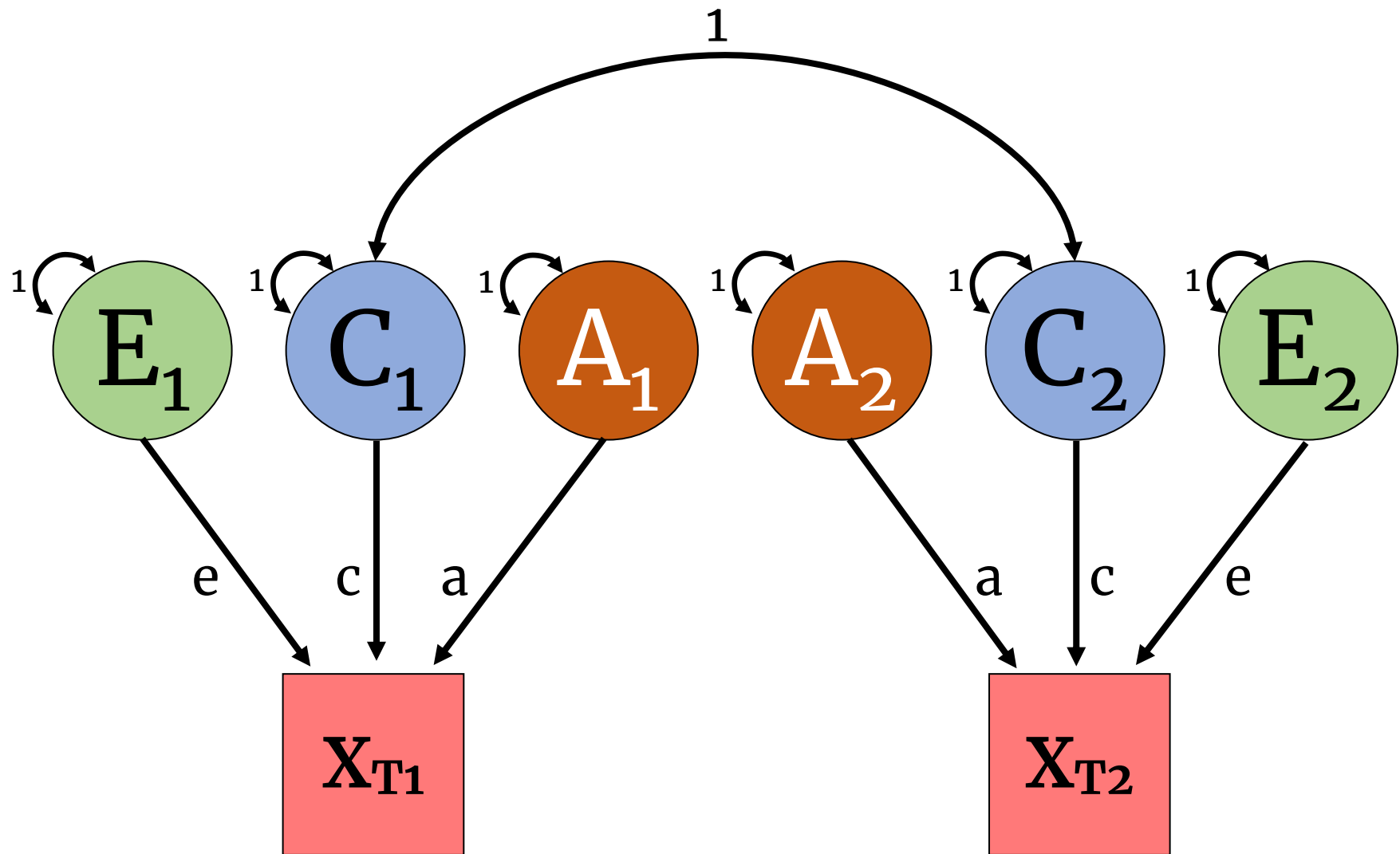
A = Additive Genetic Effects

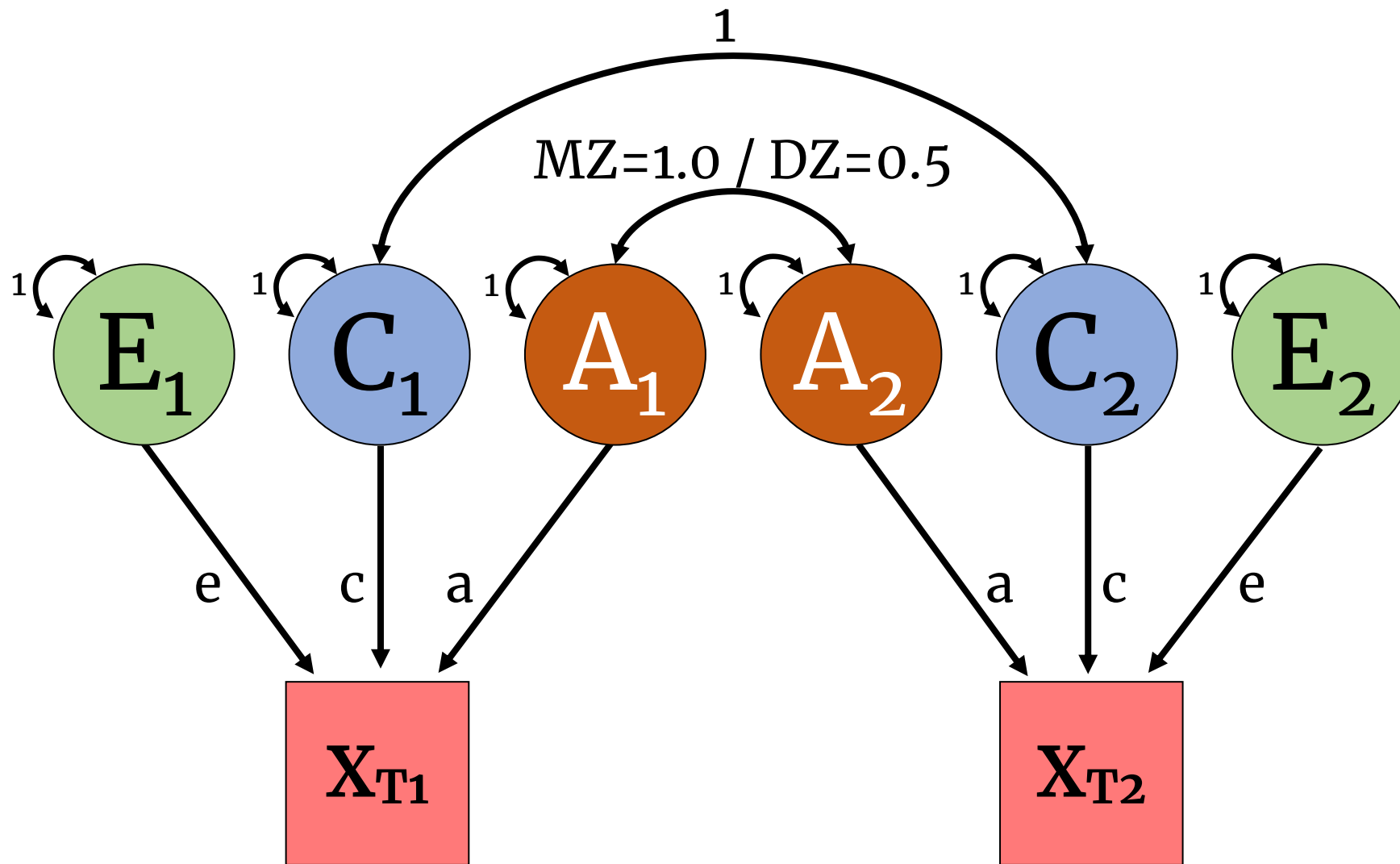
C = Common Environment

E = Unique Environment (includes measurement error)

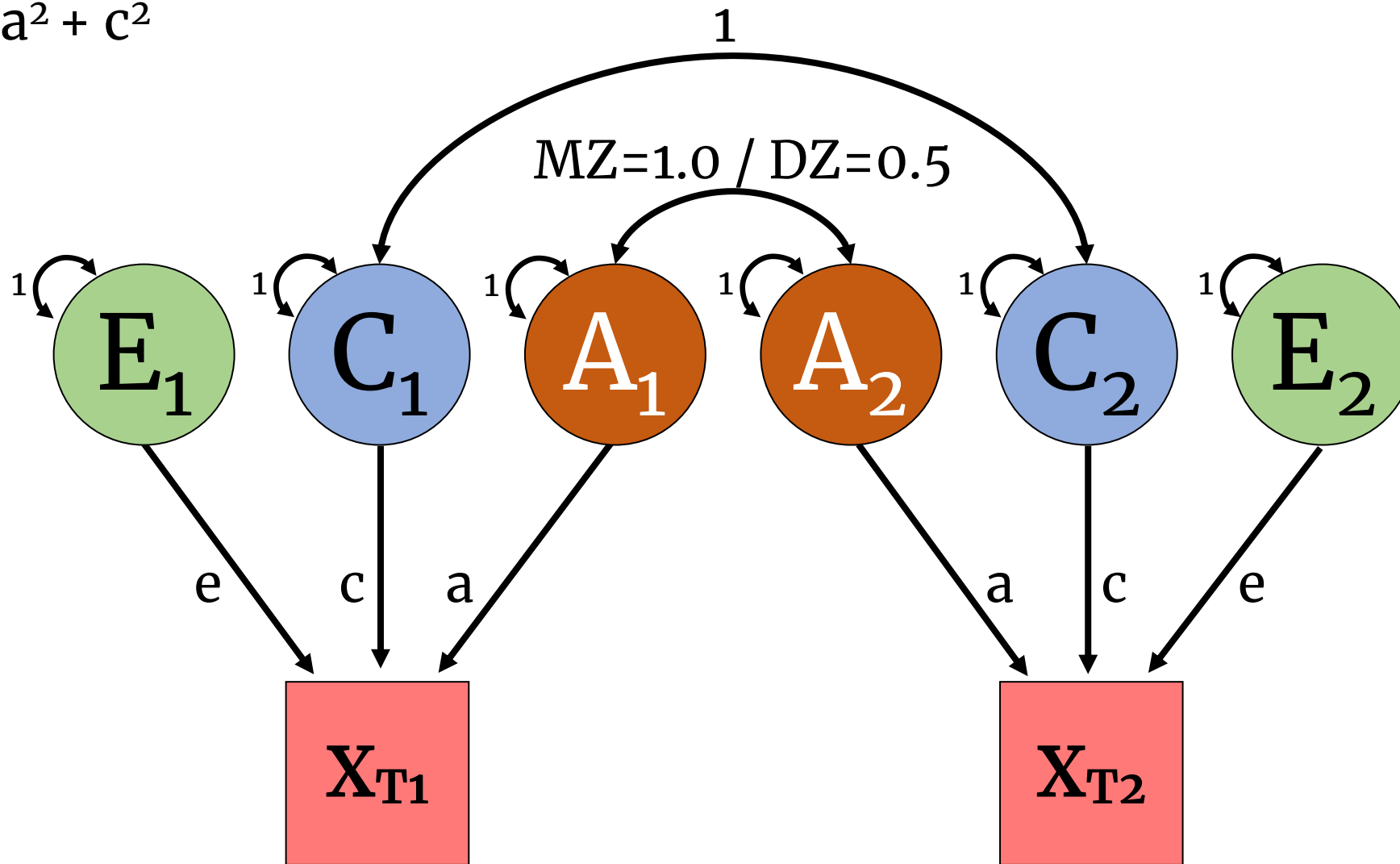






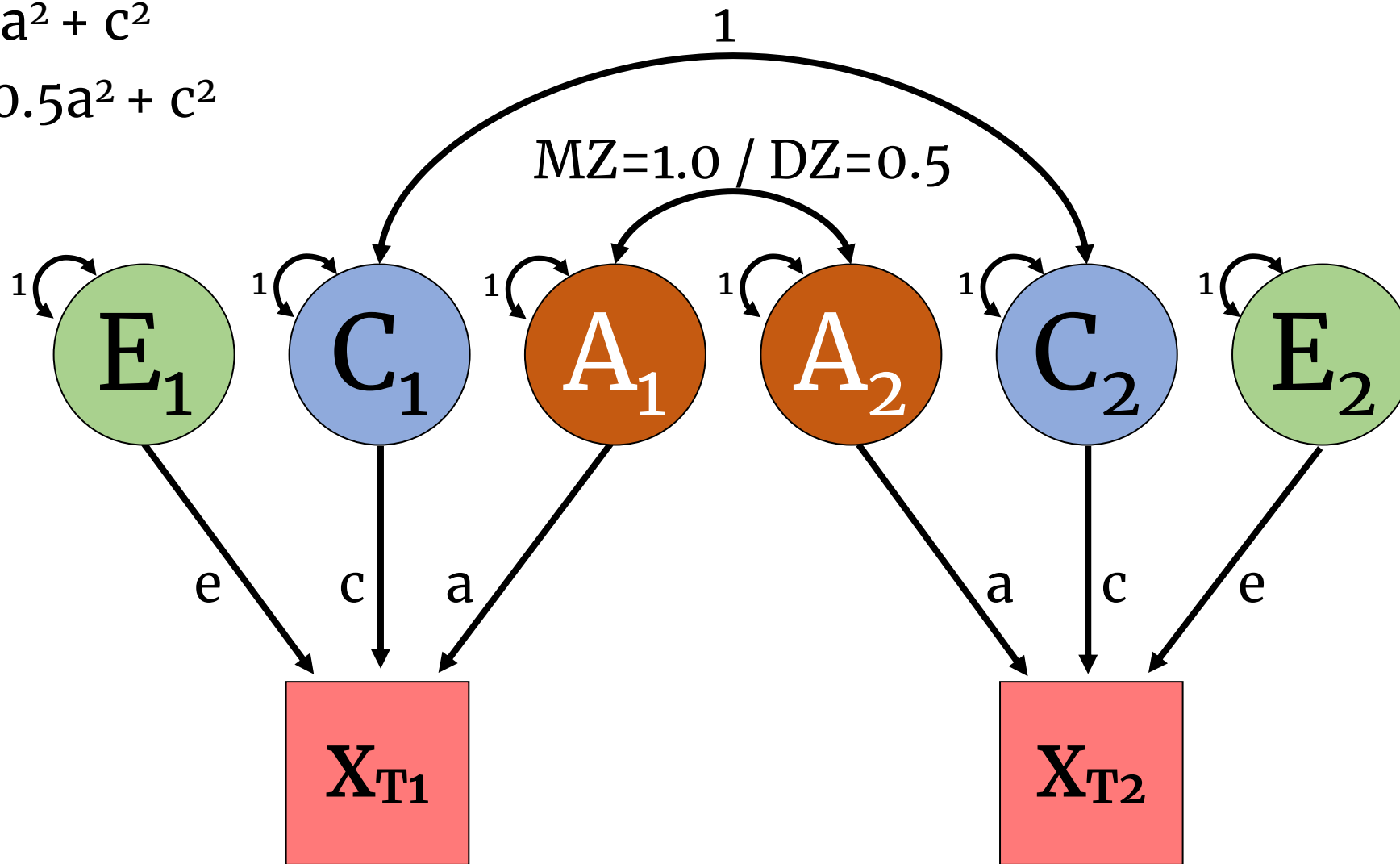


$$\text{Cov MZ} = a^2 + c^2$$



$$\text{Cov MZ} = a^2 + c^2$$

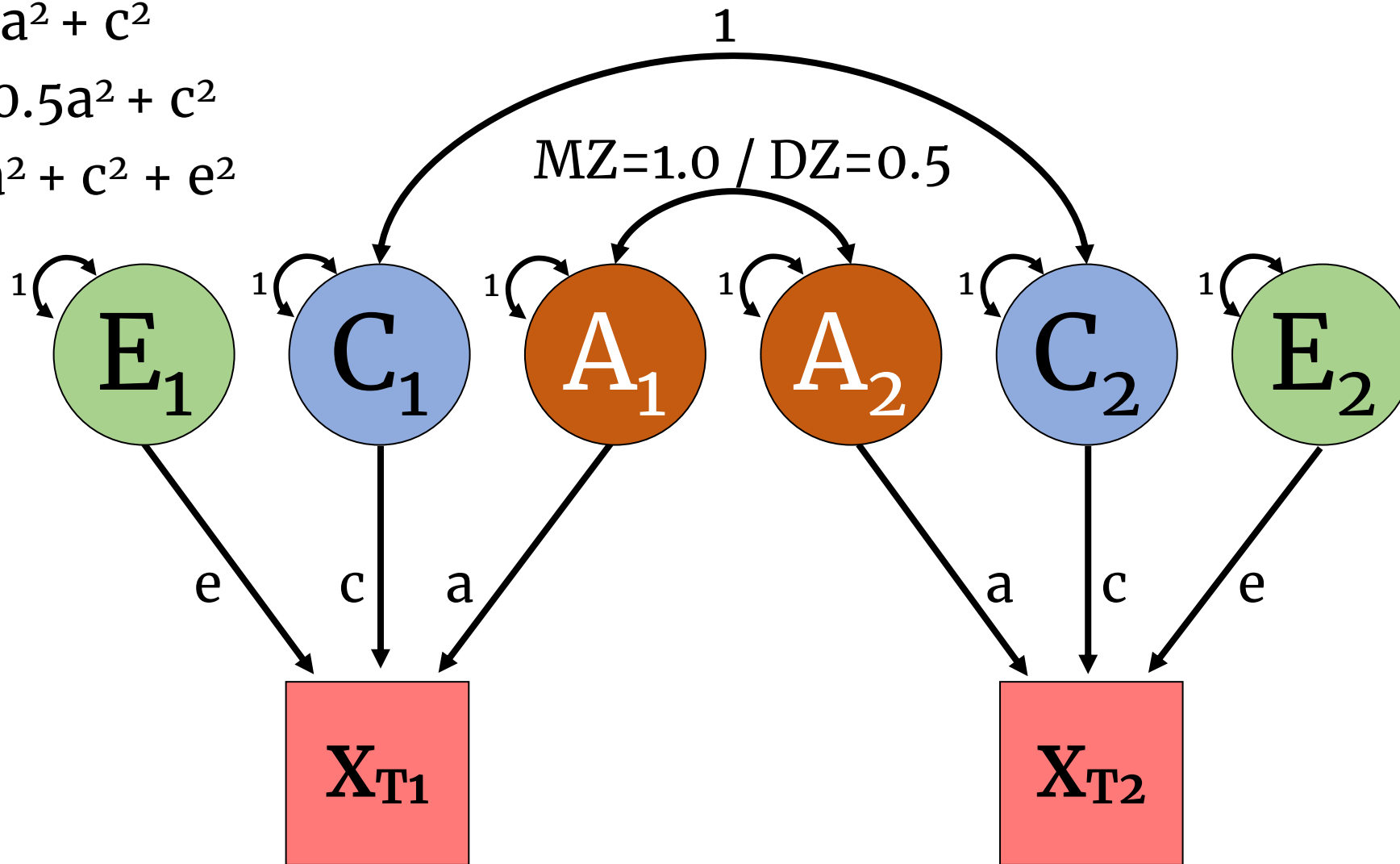
$$\text{Cov DZ} = 0.5a^2 + c^2$$



$$\text{Cov MZ} = a^2 + c^2$$

$$\text{Cov DZ} = 0.5a^2 + c^2$$

$$\text{Var}(X) = a^2 + c^2 + e^2$$



Heredity (1978), **41** (3), 249-320

MODEL-FITTING APPROACHES TO THE ANALYSIS OF HUMAN BEHAVIOUR

L. J. EAVES, KRYSTYNA A. LAST, P. A. YOUNG and N. G. MARTIN*
Department of Genetics, University of Birmingham, Birmingham B15 2TT



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THE POWER OF THE CLASSICAL TWIN STUDY

N. G. MARTIN,* L. J. EAVES,* M. J. KEARSEY* and P. DAVIES†

**Department of Genetics and †Department of Mathematical Statistics,
University of Birmingham, Birmingham B15 2TT*

Received 5.v.77



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Department of Genetics, University of Birmingham, Birmingham B15 2TT, England

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Received 5.v.77


Behavior Genetics, Vol. 23, No. 1, 1993

Testing Hypotheses About Direction of Causation Using Cross-Sectional Family Data

A. C. Heath,¹ R. C. Kessler,² M. C. Neale,³ J. K. Hewitt,³ L. J. Eaves,^{3,4} and
K. S. Kendler^{3,4}




Notes on Three Decades of Methodology Workshops

Hermine H. Maes^{1,2,3,4} 



Notes on Three Decades of Methodology Workshops

Hermine H. Maes^{1,2,3,4} 



1987: LISREL > 1990: Mx > 2008: OpenMx

Mike Neale



'classic'Mx

graphical interface



MxGui



OpenMx Team

1993 Boulder TC5



“First law of behavior genetics”:
All human behavioral traits are heritable.

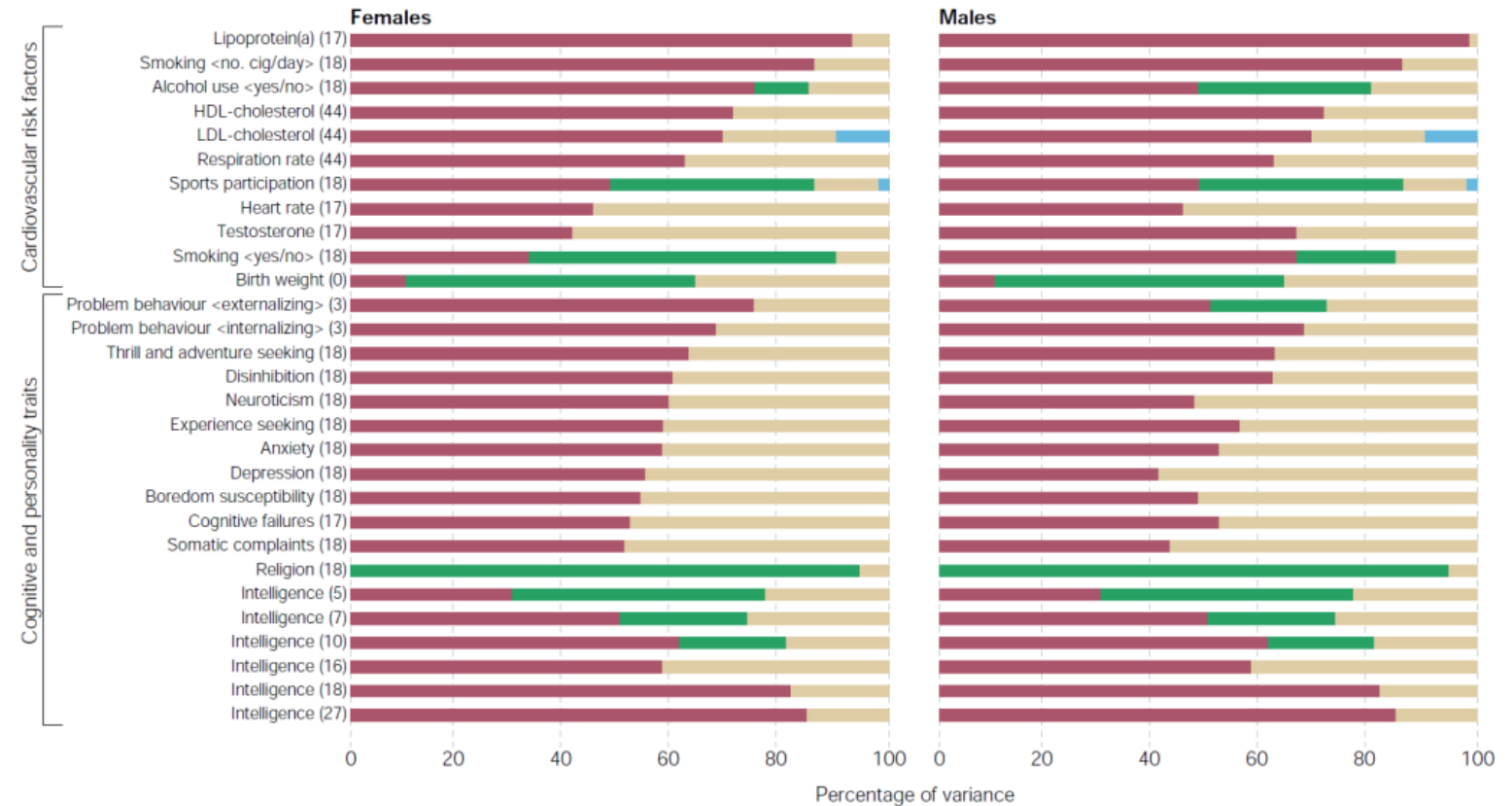


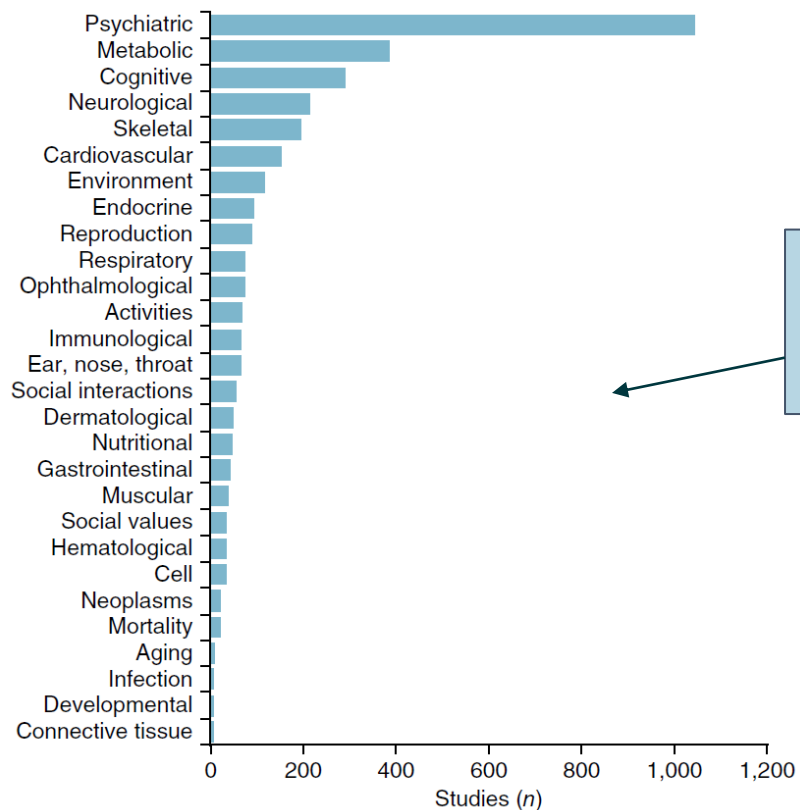
NATURE REVIEWS | GENETICS

CLASSICAL TWIN STUDIES AND BEYOND

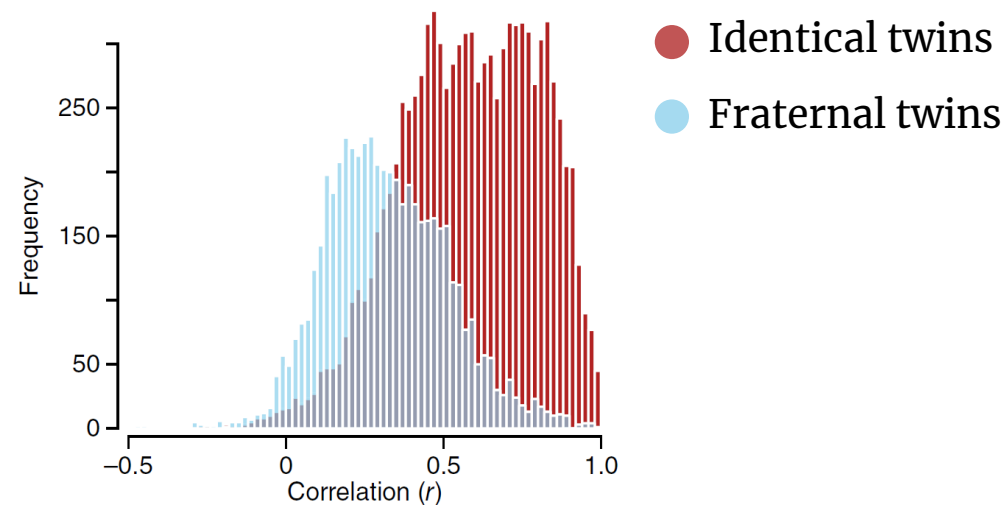
Dorret Boomsma*, Andreas Busjahn[†] and Leena Peltonen[§]

■ Additive genetic influences
■ Common environment
■ Unique environment





All twin studies
between 1958
& 2012



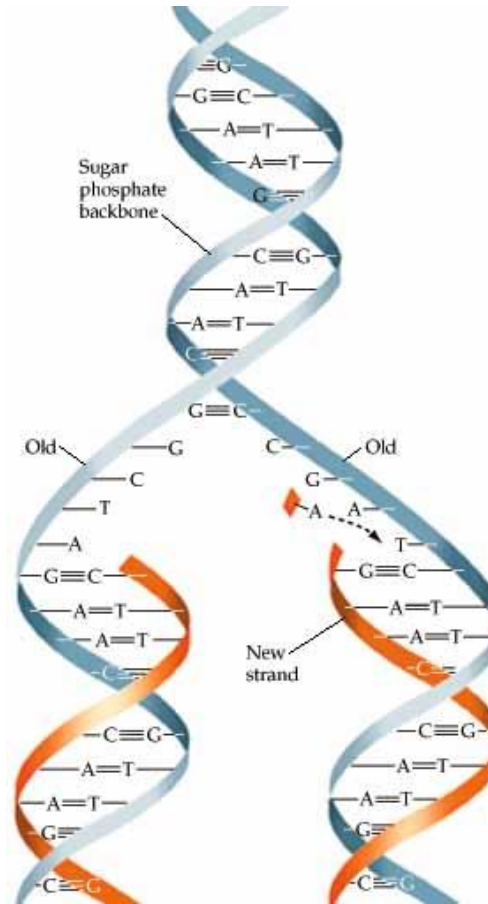
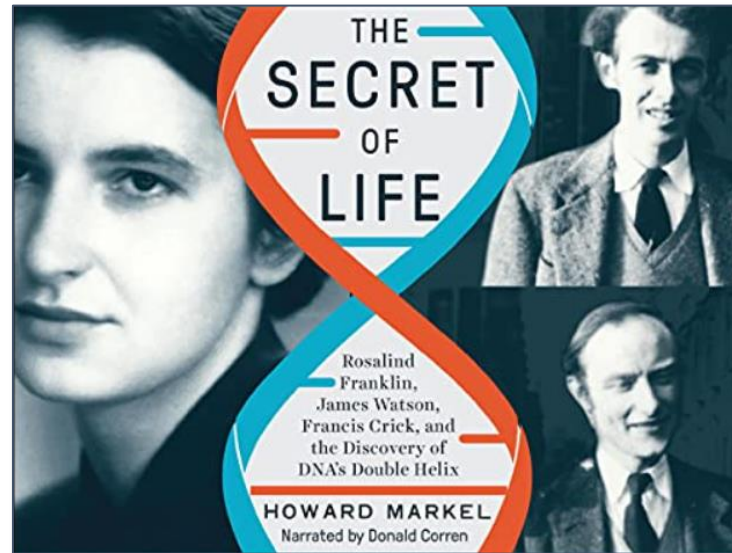
nature genetics

Meta-analysis of the heritability of human traits based on fifty years of twin studies

Tinca J C Polderman^{1,10}, Beben Benyamin^{2,10}, Christiaan A de Leeuw^{1,3}, Patrick F Sullivan⁴⁻⁶, Arjen van Bochoven⁷, Peter M Visscher^{2,8,11} & Danielle Posthuma^{1,9,11}



DNA = double helix!



No. 4356 April 25, 1953 NATURE

MOLECULAR STRUCTURE OF NUCLEIC ACIDS

A Structure for Deoxyribose Nucleic Acid

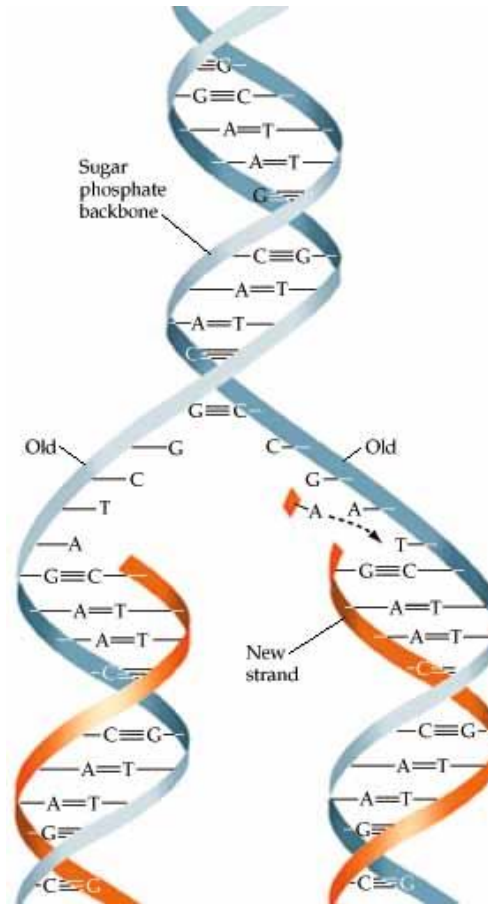
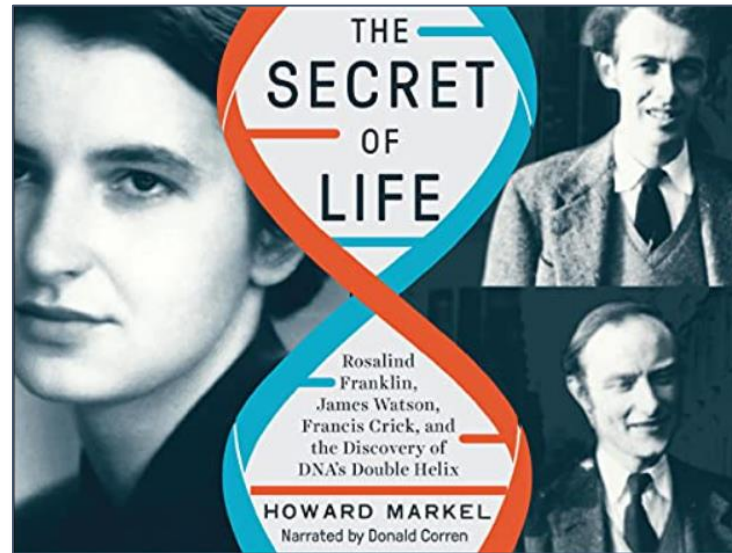


J. D. WATSON
F. H. C. CRICK

Medical Research Council Unit for the
Study of the Molecular Structure of
Biological Systems,
Cavendish Laboratory, Cambridge,
April 2,



DNA = double helix!



| | | second base in codon | | | | | | | | |
|---|---------------------|----------------------|-----|-----|-----|-----|------|---------------------|------|---|
| | | T | | C | | A | | G | | |
| T | first base in codon | TTT | Phe | TCT | Ser | TAT | Tyr | TGT | Cys | T |
| | | TTC | Phe | TCC | Ser | TAC | Tyr | TGC | Cys | C |
| | | TTA | Leu | TCA | Ser | TAA | stop | TGA | stop | A |
| | | TTG | Leu | TCG | Ser | TAG | stop | TGG | Trp | G |
| C | | CTT | Leu | CCT | Pro | CAT | His | CGT | Arg | T |
| | | CTC | Leu | CCC | Pro | CAC | His | CGC | Arg | C |
| | | CTA | Leu | CCA | Pro | CAA | Gln | CGA | Arg | A |
| | | CTG | Leu | CCG | Pro | CAG | Gln | CGG | Arg | G |
| A | | ATT | Ile | ACT | Thr | AAT | Asn | AGT | Ser | T |
| | | ATC | Ile | ACC | Thr | AAC | Asn | AGC | Ser | C |
| | | ATA | Ile | ACA | Thr | AAA | Lys | AGA | Arg | A |
| | | ATG | Met | ACG | Thr | AAG | Lys | AGG | Arg | G |
| G | | GTT | Val | GCT | Ala | GAT | Asp | GGT | Gly | T |
| | | GTC | Val | GCC | Ala | GAC | Asp | GGC | Gly | C |
| | | GTA | Val | GCA | Ala | GAA | Glu | GGA | Gly | A |
| | | GTG | Val | GCG | Ala | GAG | Glu | GGG | Gly | G |
| | | | | | | | | third base in codon | | |

There are 20 amino-acids coded for in three letter words called “codons”



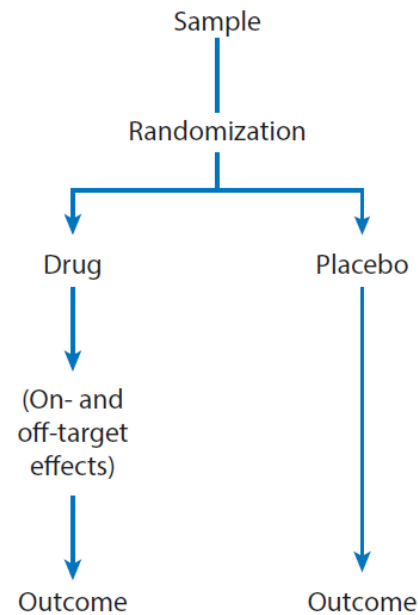
Mendelian Randomization: New Applications in the Coming Age of Hypothesis-Free Causality

David M. Evans^{1,2} and George Davey Smith²

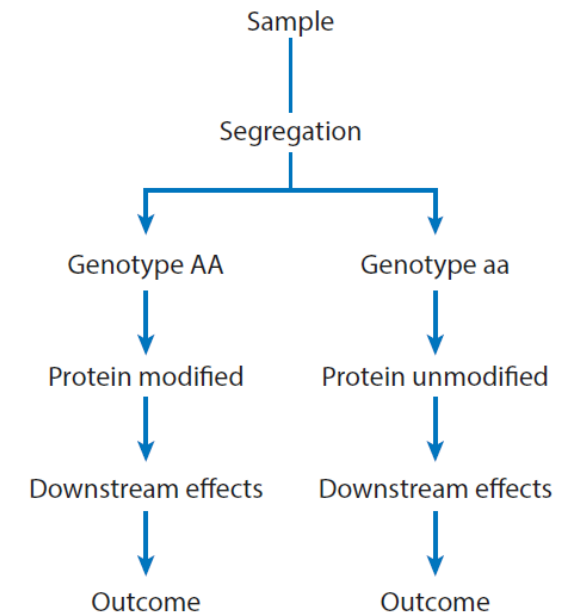
www.annualreviews.org



Randomized controlled trial



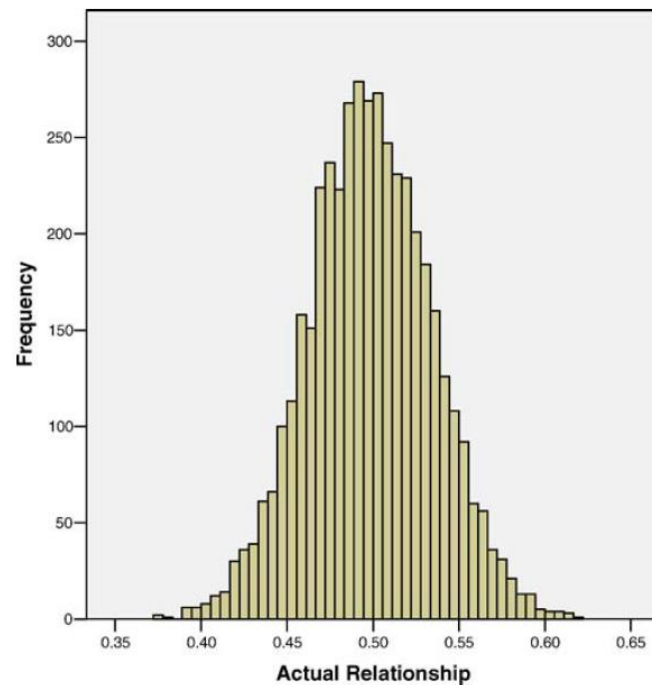
Mendelian randomization



Assumption-Free Estimation of Heritability from Genome-Wide Identity-by-Descent Sharing between Full Siblings

Peter M. Visscher*, Sarah E. Medland, Manuel A. R. Ferreira, Katherine I. Morley, Gu Zhu, Belinda K. Cornes, Grant W. Montgomery, Nicholas G. Martin

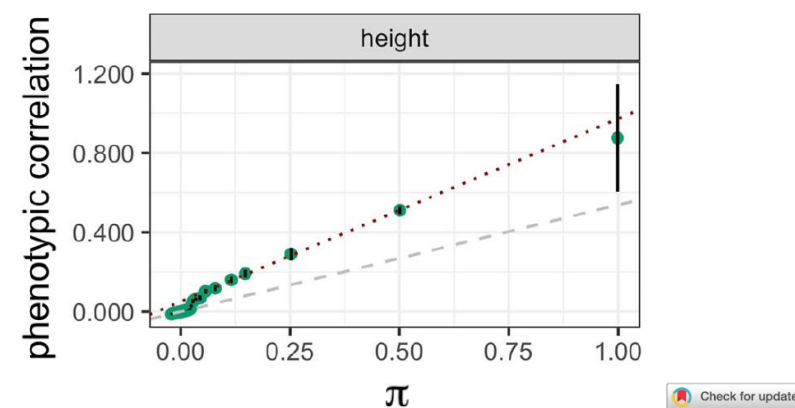
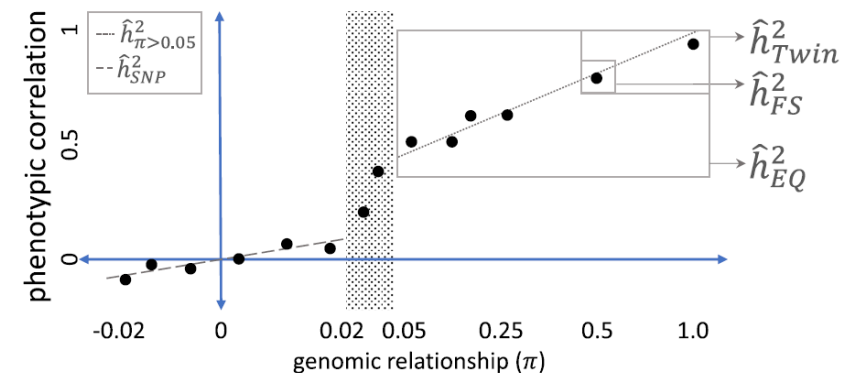
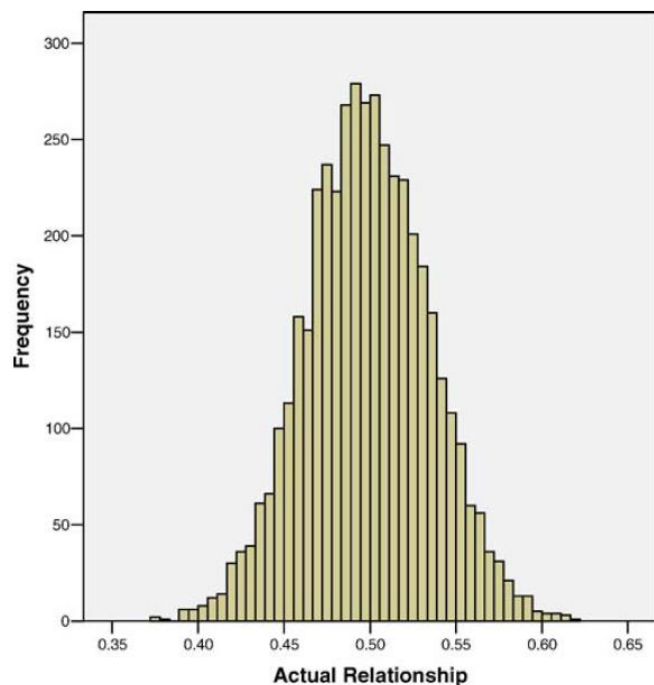
Genetic Epidemiology Group, Queensland Institute of Medical Research, Brisbane, Australia



Assumption-Free Estimation of Heritability from Genome-Wide Identity-by-Descent Sharing between Full Siblings

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ARTICLE

<https://doi.org/10.1038/s41467-021-21283-4>

OPEN

Phenotypic covariance across the entire spectrum of relatedness for 86 billion pairs of individuals

Kathryn E. Kemper¹, Loic Yengo¹, Zhili Zheng¹, Abdel Abdellaoui², Matthew C. Keller^{3,4}, Michael E. Goddard^{5,6}, Naomi R. Wray^{1,7}, Jian Yang¹ & Peter M. Visscher^{1,7}



The Future of Genetic Studies of Complex Human Diseases

Neil Risch and Kathleen Merikangas

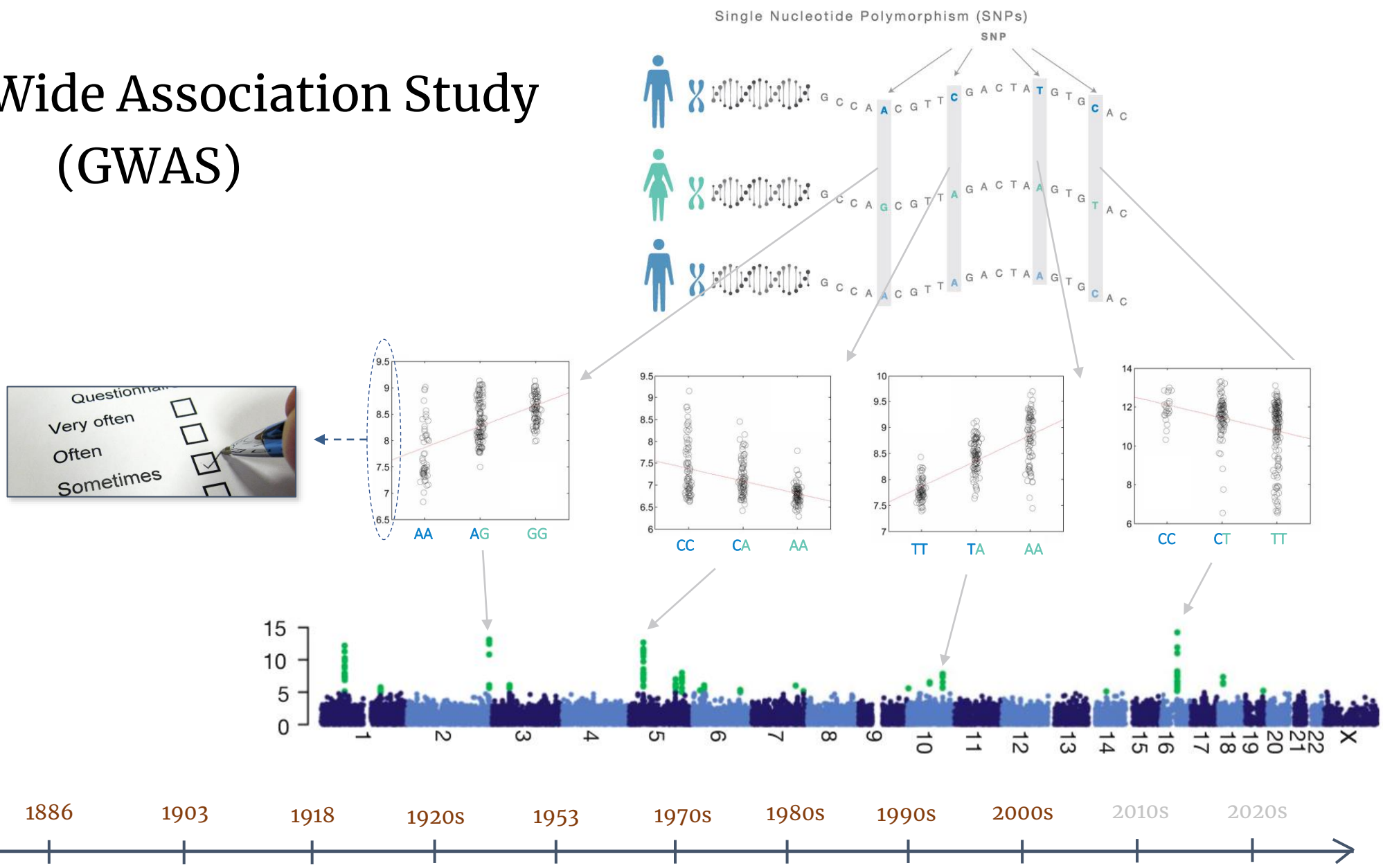
| Linkage | | | | | Association | | | |
|--------------------------------------|--|--|-------------------------------------|--|---|---------|-----------|---------|
| Genotypic risk ratio (γ) | Frequency of disease allele A (p) | Probability of allele sharing (Y) | No. of families required (N) | Probability of transmitting disease allele A $P(\text{tr-A})$ | Singletons | | Sib pairs | |
| | | | | | Proportion of heterozygous parents (Het) | (N) | (Het) | (N) |
| 4.0 | 0.01 | 0.520 | 4260 | 0.800 | 0.048 | 1098 | 0.112 | 235 |
| | 0.10 | 0.597 | 185 | 0.800 | 0.346 | 150 | 0.537 | 48 |
| | 0.50 | 0.576 | 297 | 0.800 | 0.500 | 103 | 0.424 | 61 |
| | 0.80 | 0.529 | 2013 | 0.800 | 0.235 | 222 | 0.163 | 161 |
| 2.0 | 0.01 | 0.502 | 296,710 | 0.667 | 0.029 | 5823 | 0.043 | 1970 |
| | 0.10 | 0.518 | 5382 | 0.667 | 0.245 | 695 | 0.323 | 264 |
| | 0.50 | 0.526 | 2498 | 0.667 | 0.500 | 340 | 0.474 | 180 |
| | 0.80 | 0.512 | 11,917 | 0.667 | 0.267 | 640 | 0.217 | 394 |
| 1.5 | 0.01 | 0.501 | 4,620,807 | 0.600 | 0.025 | 19,320 | 0.031 | 7776 |
| | 0.10 | 0.505 | 67,816 | 0.600 | 0.197 | 2218 | 0.253 | 941 |
| | 0.50 | 0.510 | 17,997 | 0.600 | 0.500 | 949 | 0.490 | 484 |
| | 0.80 | 0.505 | 67,816 | 0.600 | 0.286 | 1663 | 0.253 | 941 |

Comparison of linkage and association studies. Number of families needed for identification of a disease gene.

Thus, the primary limitation of genome-wide association tests is not a statistical one but a technological one. A large number of genes (up to 100,000) and polymorphisms (preferentially ones that create alterations in derived proteins or their expression) must first be identified, and an extremely large number of such polymorphisms will need to be tested. Although testing such a large number of polymorphisms on several hundred, or even a thousand families, might currently seem implausible in scope, more efficient methods of screening a large number of polymorphisms (for example, sample pooling) may be possible.



Genome-Wide Association Study (GWAS)



PRESS RELEASES / 01.26.16

Genetic study provides first-ever insight into biological origin of schizophrenia



2016

ARTICLE

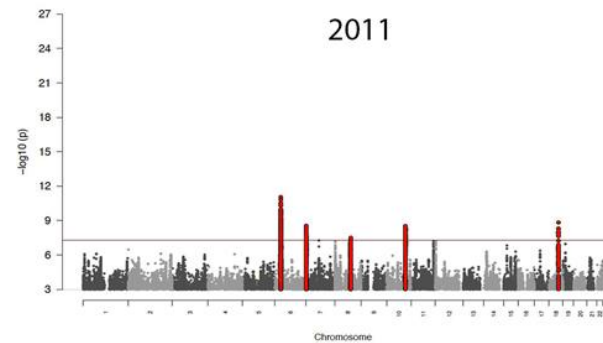
doi:10.1038/nature16549

Schizophrenia risk from complex variation of complement component 4

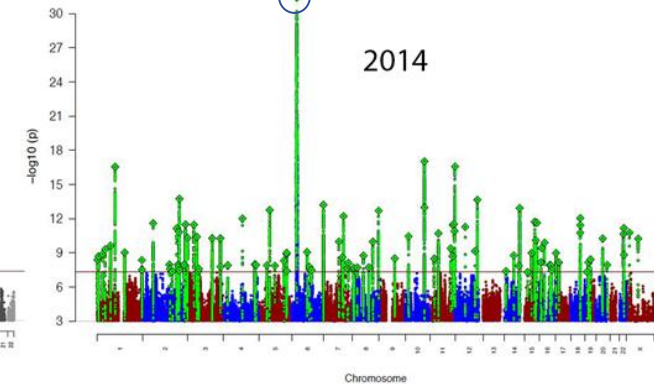
Aswin Sekar^{1,2,3}, Allison R. Bilal^{4,5}, Heather de Rivera^{1,2}, Avery Davis^{1,2}, Timothy R. Hammond⁴, Nolan Kamitaki^{1,2}, Katherine Tooley^{1,2}, Jessy Presumey⁷, Matthew Baum^{10,11}, Vanessa Van Doren¹, Giulio Genovese^{1,2}, Samuel A. Rose², Robert E. Handsaker^{1,2}, Schizophrenia Working Group of the Psychiatric Genomics Consortium*, Mark J. Daly^{2,6}, Michael C. Carroll², Beth Stevens^{2,8} & Steven A. McCarroll^{1,2}

Schizophrenia is a heritable brain illness with unknown pathogenic mechanisms. Schizophrenia's strongest genetic association at a population level involves variation in the major histocompatibility complex (MHC) locus, but the genes and molecular mechanisms accounting for this have been challenging to identify. Here we show that this association arises in part from many structurally diverse alleles of the complement component 4 (C4) genes. We found that these alleles generated widely varying levels of C4A and C4B expression in the brain, with each common C4 allele associating with schizophrenia in proportion to its tendency to generate greater expression of C4A. Human C4 protein localized to neuronal synapses, dendrites, axons, and cell bodies. In mice, C4 mediated synapse elimination during postnatal development. These results implicate excessive complement activity in the development of schizophrenia and may help explain the reduced numbers of synapses in the brains of individuals with schizophrenia.

Influences “synaptic pruning” — the elimination of connections between neurons



N ~ 50,000

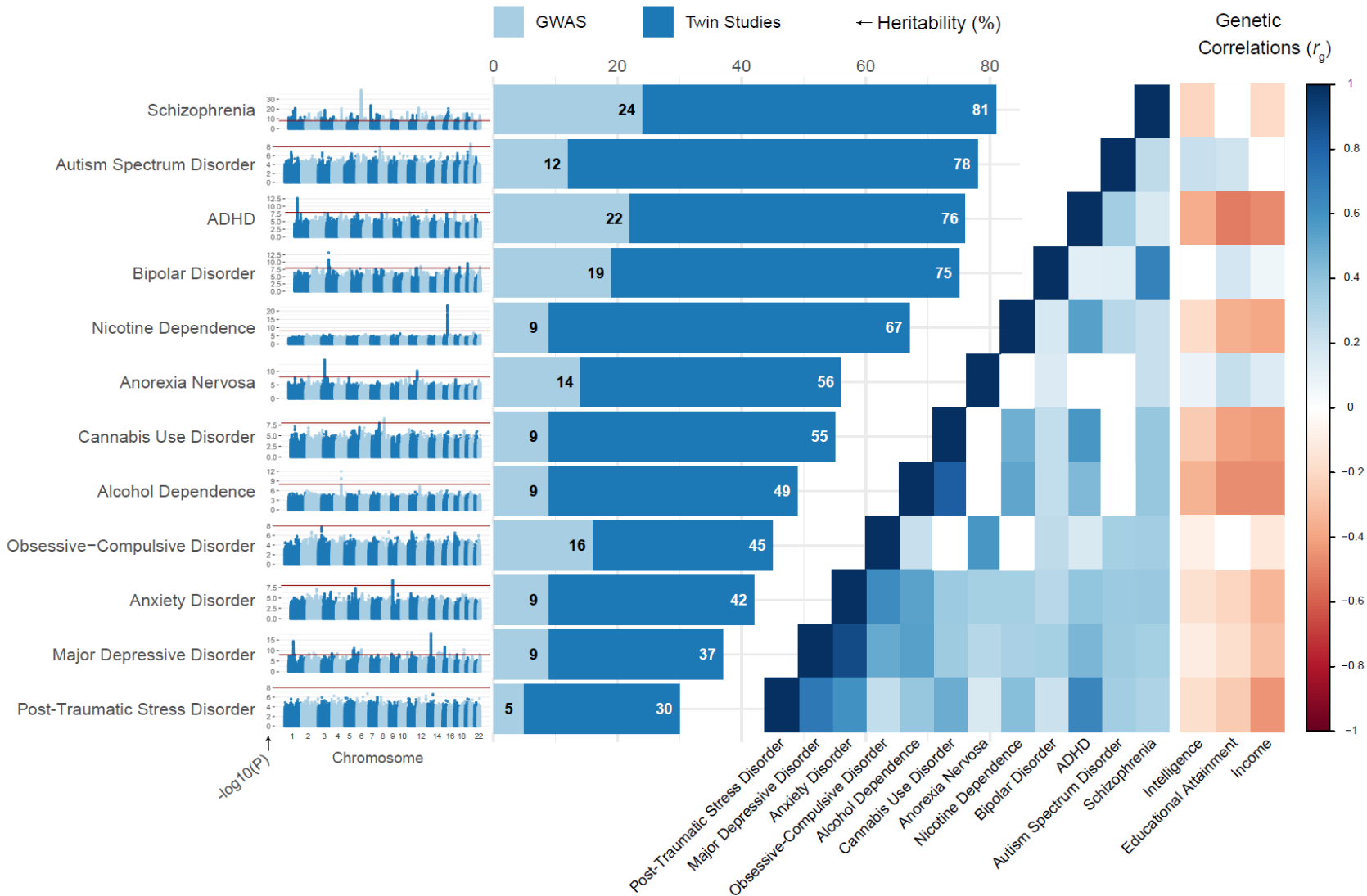


N ~ 150,000



Genetica en psychiatrie

A. Abdellaoui, K.J.H. Verweij

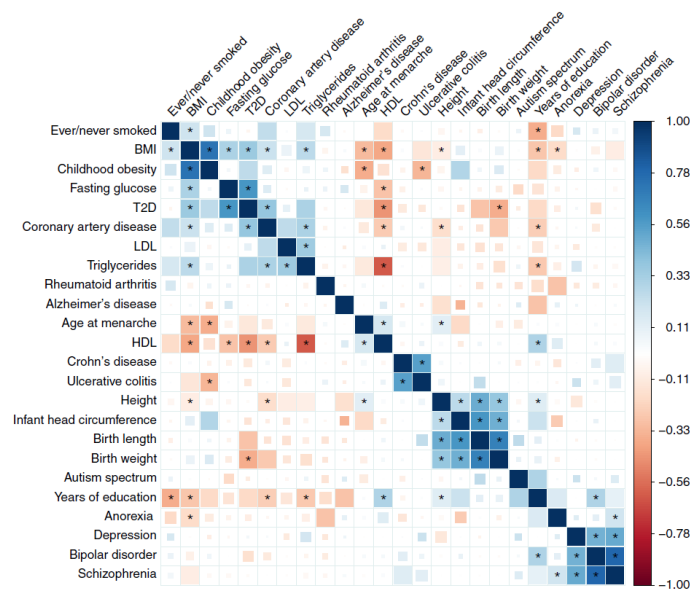


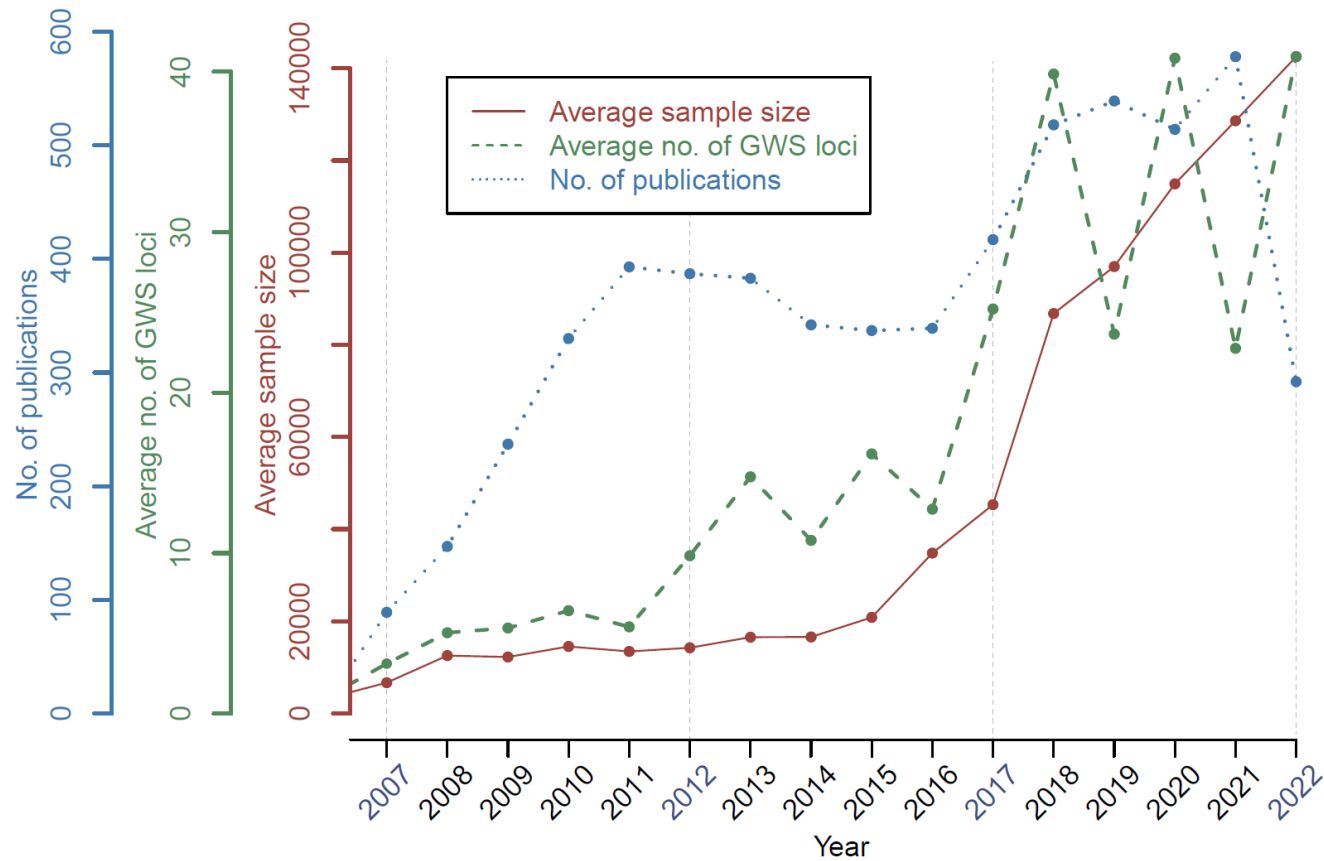
LD Score regression distinguishes confounding from polygenicity in genome-wide association studies

Brendan K Bulik-Sullivan¹⁻³, Po-Ru Loh^{1,4}, Hilary K Finucane^{4,5}, Stephan Ripke^{2,3}, Jian Yang⁶, Schizophrenia Working Group of the Psychiatric Genomics Consortium⁷, Nick Patterson¹, Mark J Daly¹⁻³, Alkes L Price^{1,4,8} & Benjamin M Neale¹⁻³

An atlas of genetic correlations across human diseases and traits

Brendan Bulik-Sullivan^{1-3,9}, Hilary K Finucane^{4,9}, Verner Anttila¹⁻³, Alexander Gusev^{5,6}, Felix R Day⁷, Po-Ru Loh^{1,5}, ReproGen Consortium⁸, Psychiatric Genomics Consortium⁸, Genetic Consortium for Anorexia Nervosa of the Wellcome Trust Case Control Consortium^{3,8}, Laramie Duncan¹⁻³, John R B Perry⁷, Nick Patterson¹, Elise B Robinson¹⁻³, Mark J Daly¹⁻³, Alkes L Price^{1,5,6,10} & Benjamin M Neale^{1-3,10}





The American Journal of Human Genetics
REVIEW

15 years of GWAS discovery: Realizing the promise

Abdel Abdellaoui,^{1,*} Loic Yengo,² Karin J.H. Verweij,¹ and Peter M. Visscher²



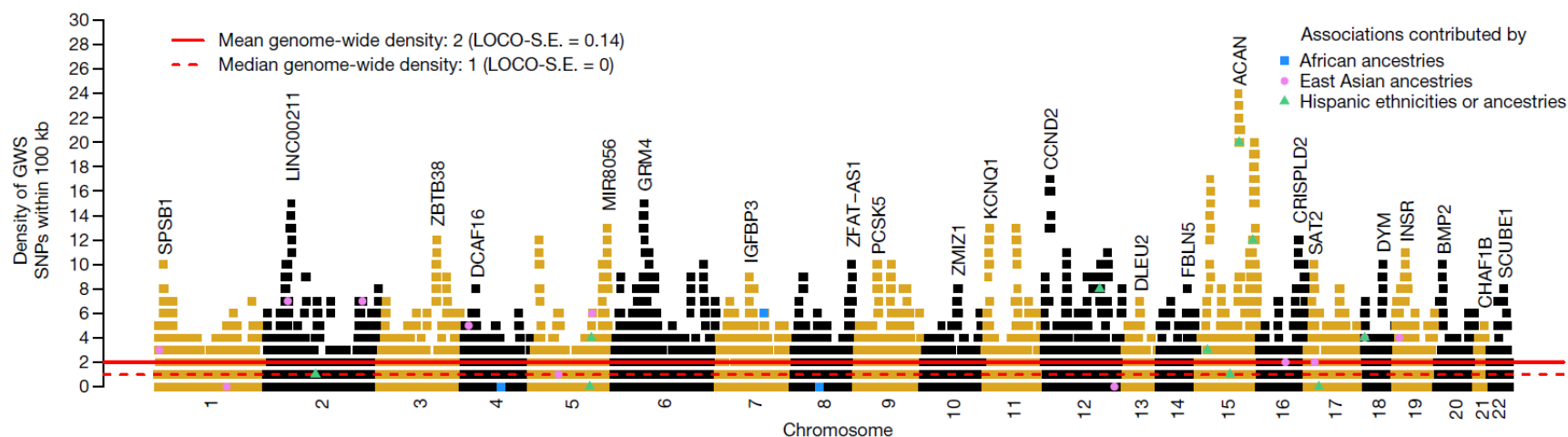
Article

A saturated map of common genetic variants associated with human height

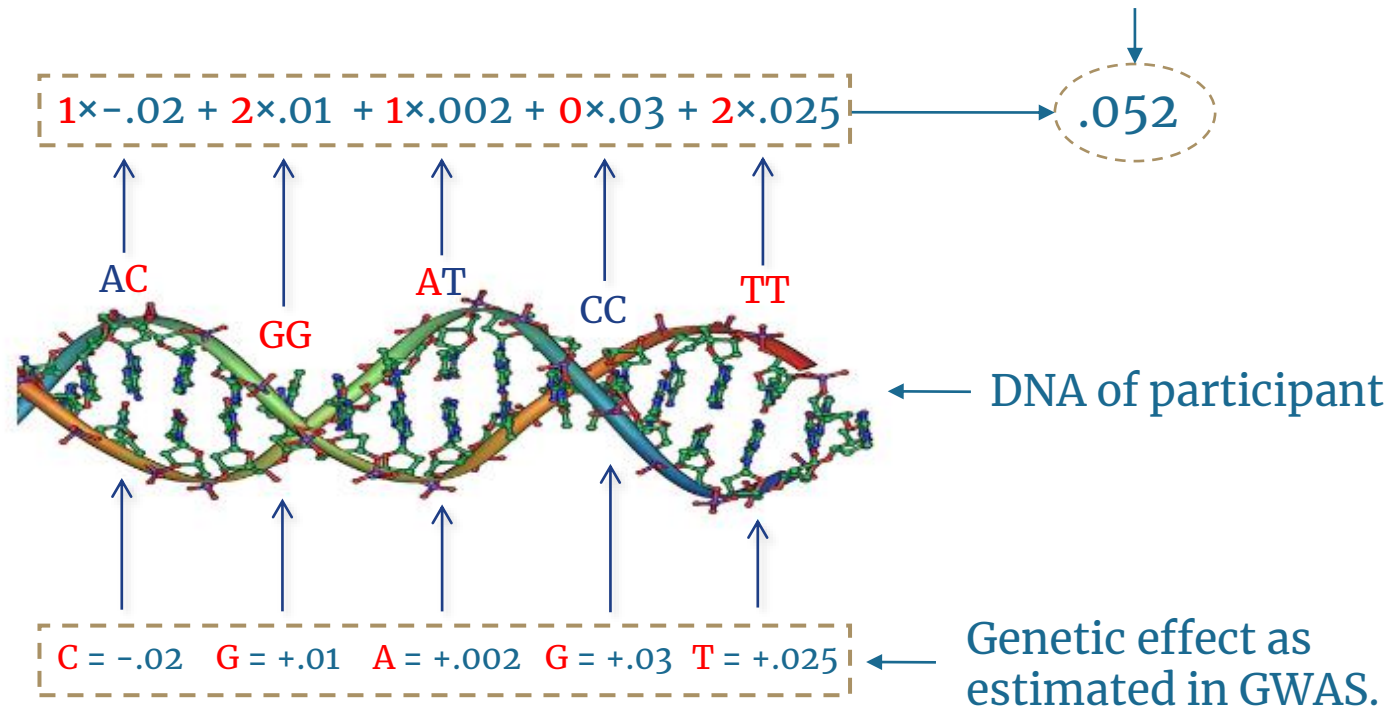
Nature | Vol 610 | 27 October 2022



N = 5.4 million



Polygenic Score



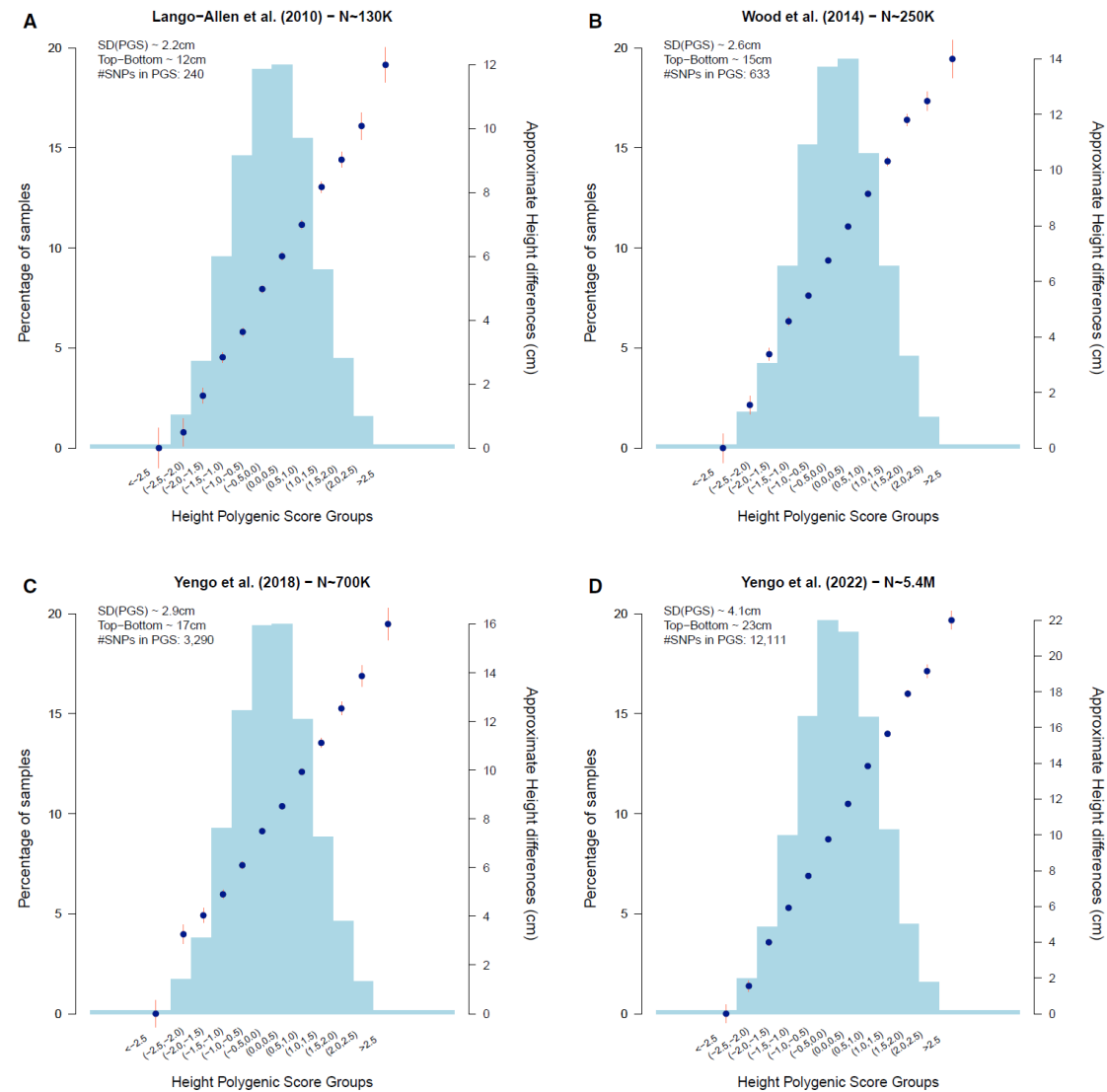
Polygenic Score Prediction

The American Journal of Human Genetics

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REVIEW



Polygenic Score Prediction

SD of outcome around the prediction:

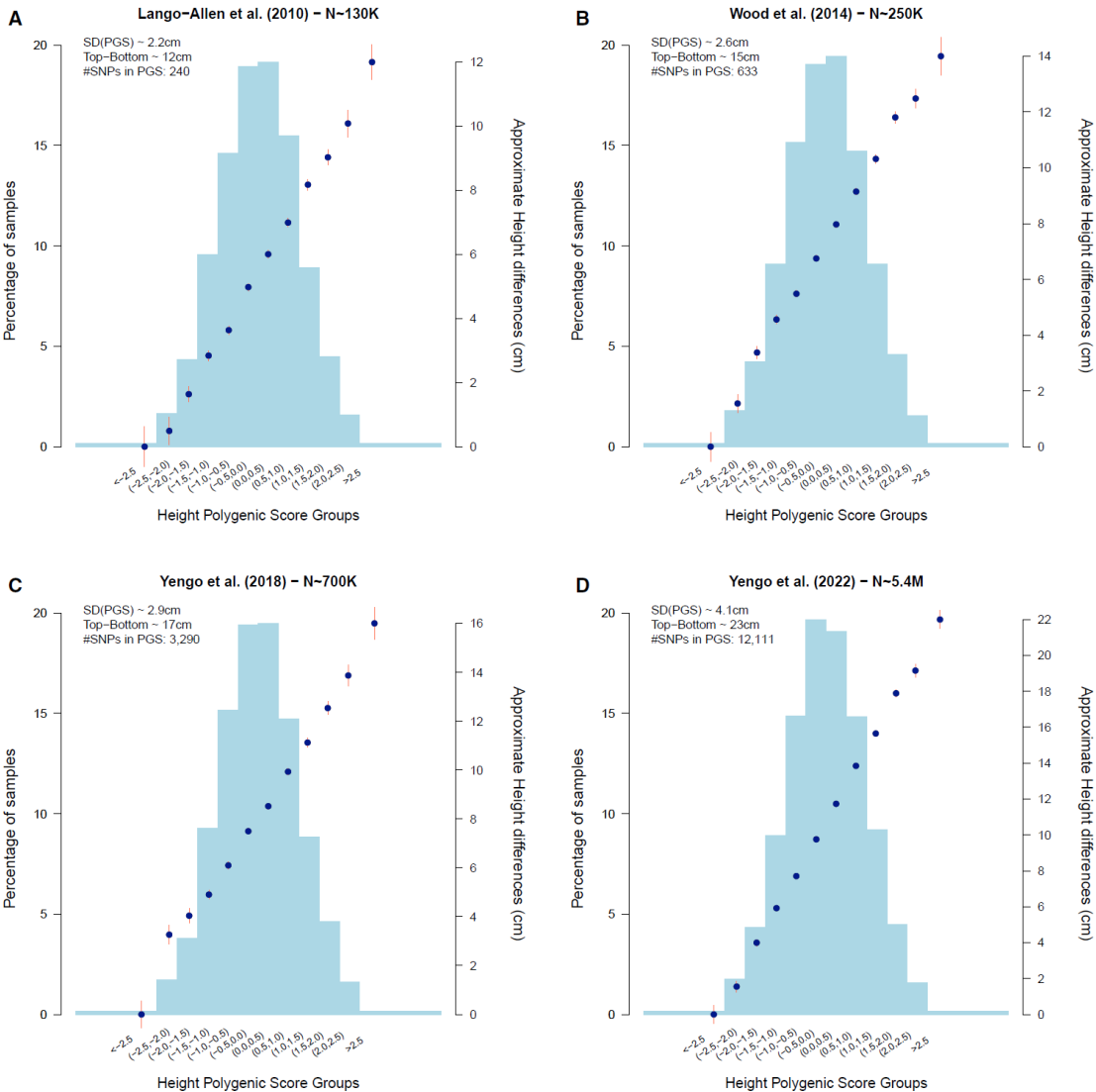
$$\sigma_Y \sqrt{1 - R^2}$$

The American Journal of Human Genetics

REVIEW

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Polygenic Score Prediction

SD of outcome around the prediction:

$$\sigma_Y \sqrt{1 - R^2}$$

Upper bound (maximum predictive power):

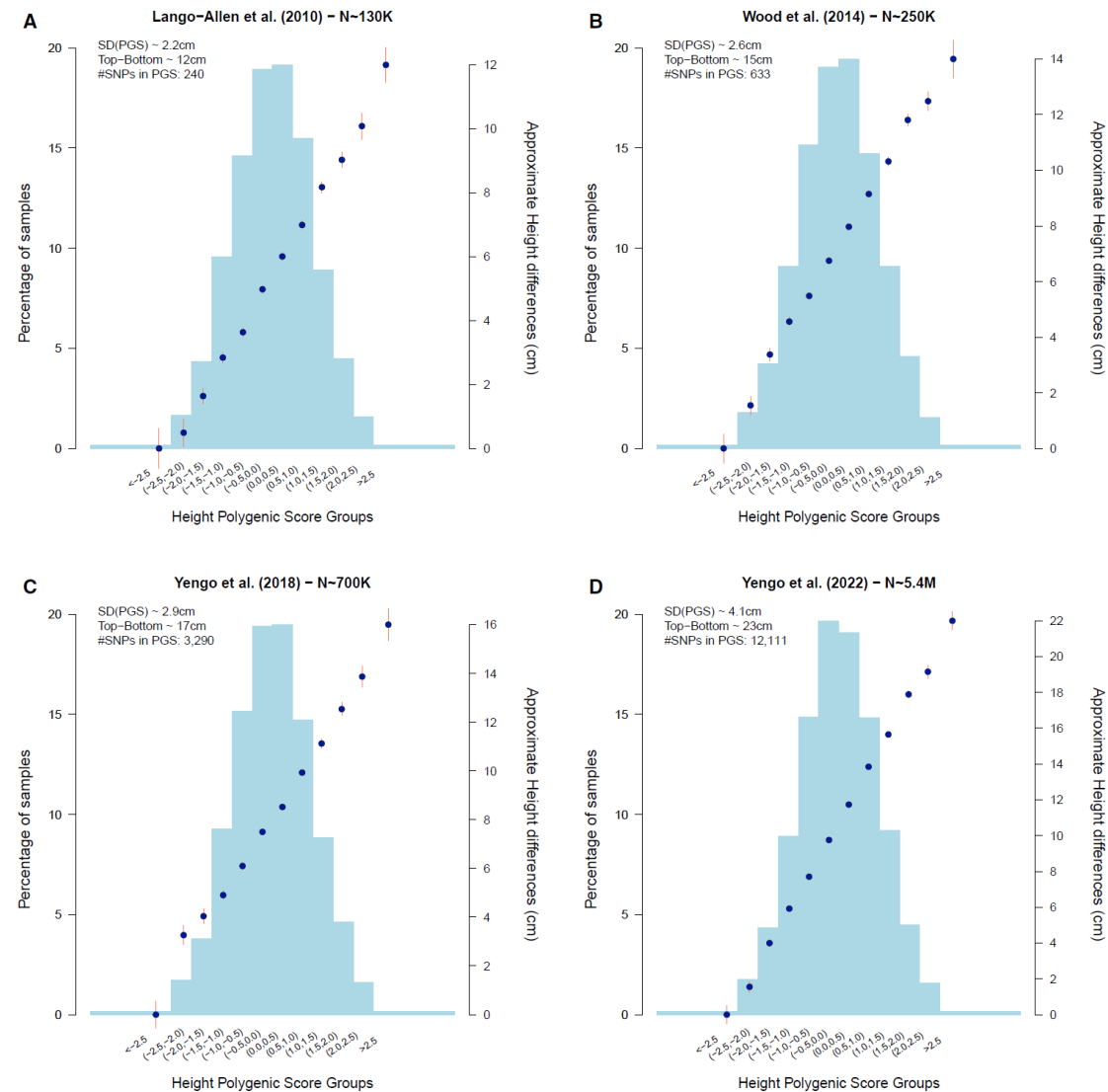
$$\sigma_Y \sqrt{1 - h^2}$$

The American Journal of Human Genetics

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Abdel Abdellaoui,^{1,*} Loic Yengo,² Karin J.H. Verweij,¹ and Peter M. Visscher²

REVIEW



Polygenic Score Prediction

SD of outcome around the prediction:

$$\sigma_Y \sqrt{1 - R^2}$$

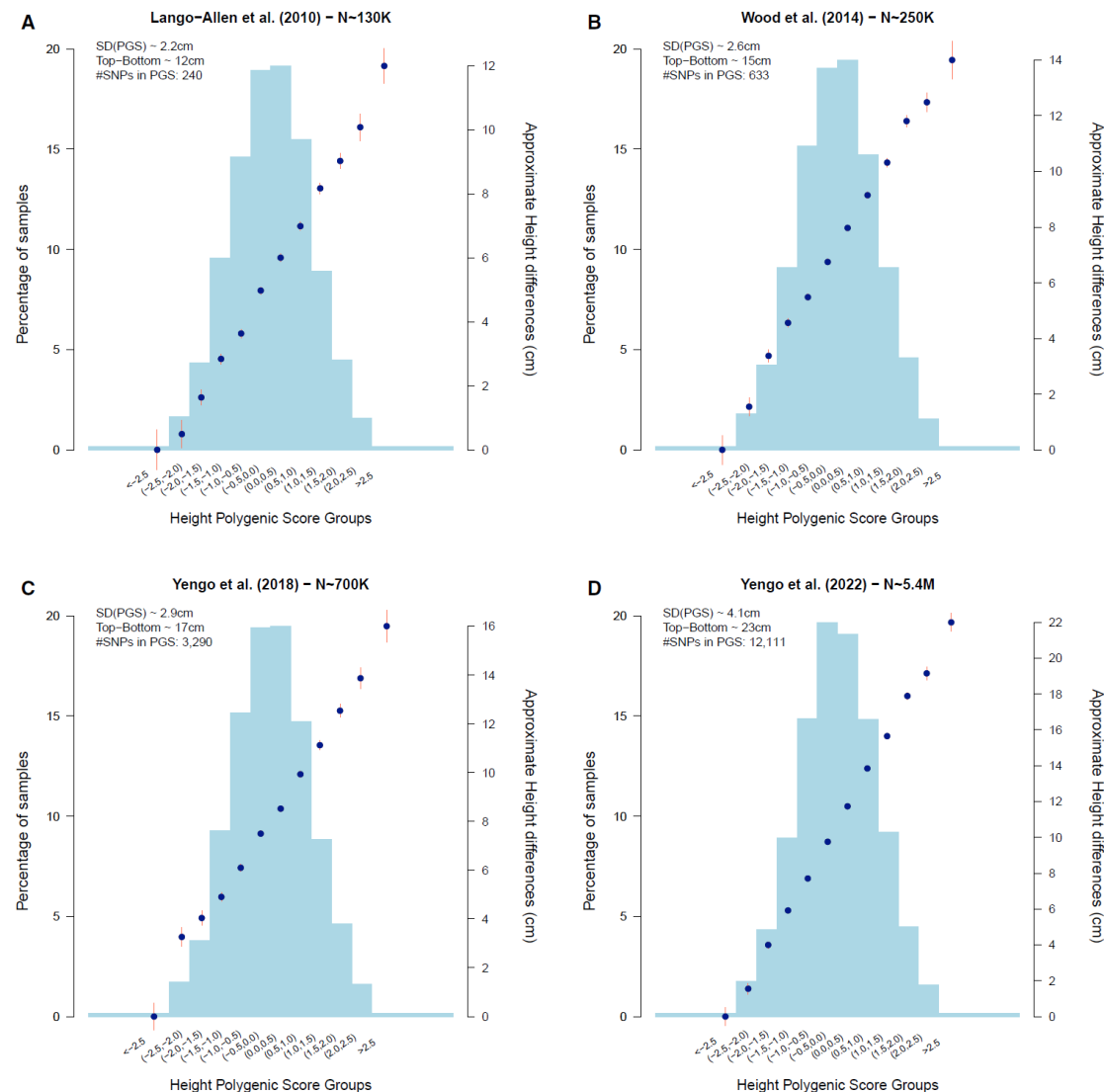
Upper bound (maximum predictive power):

$$\sigma_Y \sqrt{1 - h^2}$$

Height has heritability of ~0.8 and standard deviation of ~6.5 cm

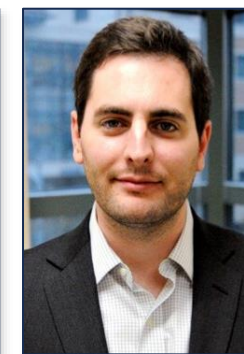
$$6.5\text{cm} \times \sqrt{1 - 0.8} \approx 3\text{cm}$$

Equivalent to 95% confidence interval of ~12cm



Genomic structural equation modelling provides insights into the multivariate genetic architecture of complex traits

Andrew D. Grotzinger^{1*}, Mijke Rhemtulla², Ronald de Vlaming^{3,4}, Stuart J. Ritchie^{5,6}, Travis T. Mallard¹, W. David Hill^{5,6}, Hill F. Ip⁷, Riccardo E. Marioni^{5,8}, Andrew M. McIntosh^{5,9}, Ian J. Deary^{5,6}, Philipp D. Koellinger^{3,4}, K. Paige Harden^{1,10}, Michel G. Nivard^{7,11} and Elliot M. Tucker-Drob^{1,10,11}



Genomic structural equation modelling provides insights into the multivariate genetic architecture of complex traits

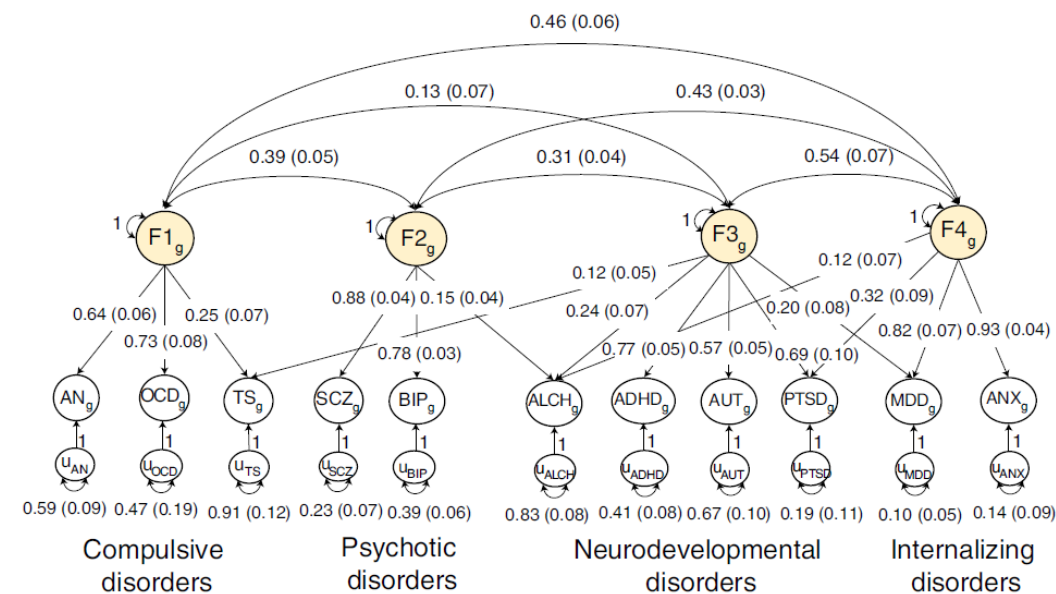
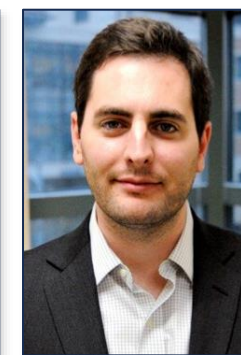
Andrew D. Grotzinger^{1*}, Mijke Rhemtulla², Ronald de Vlaming^{3,4}, Stuart J. Ritchie^{5,6}, Travis T. Mallard¹, W. David Hill^{5,6}, Hill F. Ip⁷, Riccardo E. Marioni^{5,8}, Andrew M. McIntosh^{5,9}, Ian J. Deary^{5,6}, Philipp D. Koellinger^{3,4}, K. Paige Harden^{1,10}, Michel G. Nivard^{7,11} and Elliot M. Tucker-Drob^{1,10,11}

ARTICLES

<https://doi.org/10.1038/s41588-022-01057-4>nature
genetics

Genetic architecture of 11 major psychiatric disorders at biobehavioral, functional genomic and molecular genetic levels of analysis

Andrew D. Grotzinger^{1,2}, Travis T. Mallard³, Wonuola A. Akingbuwa^{4,5}, Hill F. Ip⁴, Mark J. Adams⁶, Cathryn M. Lewis^{7,8}, Andrew M. McIntosh⁶, Jakob Grove^{9,10,11,12}, Søren Dalsgaard¹³, Klaus-Peter Lesch^{14,15,16}, Nora Strom^{17,18,19}, Sandra M. Meier^{10,20}, Manuel Mattheisen^{10,17,19,20,21,22}, Anders D. Børglum^{9,10,11}, Ole Mors^{9,23}, Gerome Breen^{7,8}, iPSYCH*, Tourette Syndrome and Obsessive Compulsive Disorder Working Group of the Psychiatric Genetics Consortium*, Bipolar Disorder Working Group of the Psychiatric Genetics Consortium*, Major Depressive Disorder Working Group of the Psychiatric Genetics Consortium*, Schizophrenia Working Group of the Psychiatric Genetics Consortium*, Phil H. Lee^{24,25}, Kenneth S. Kendler²⁶, Jordan W. Smoller^{24,25}, Elliot M. Tucker-Drob^{3,27,28} and Michel G. Nivard^{4,28}



OPEN

Within-sibship genome-wide association analyses decrease bias in estimates of direct genetic effects

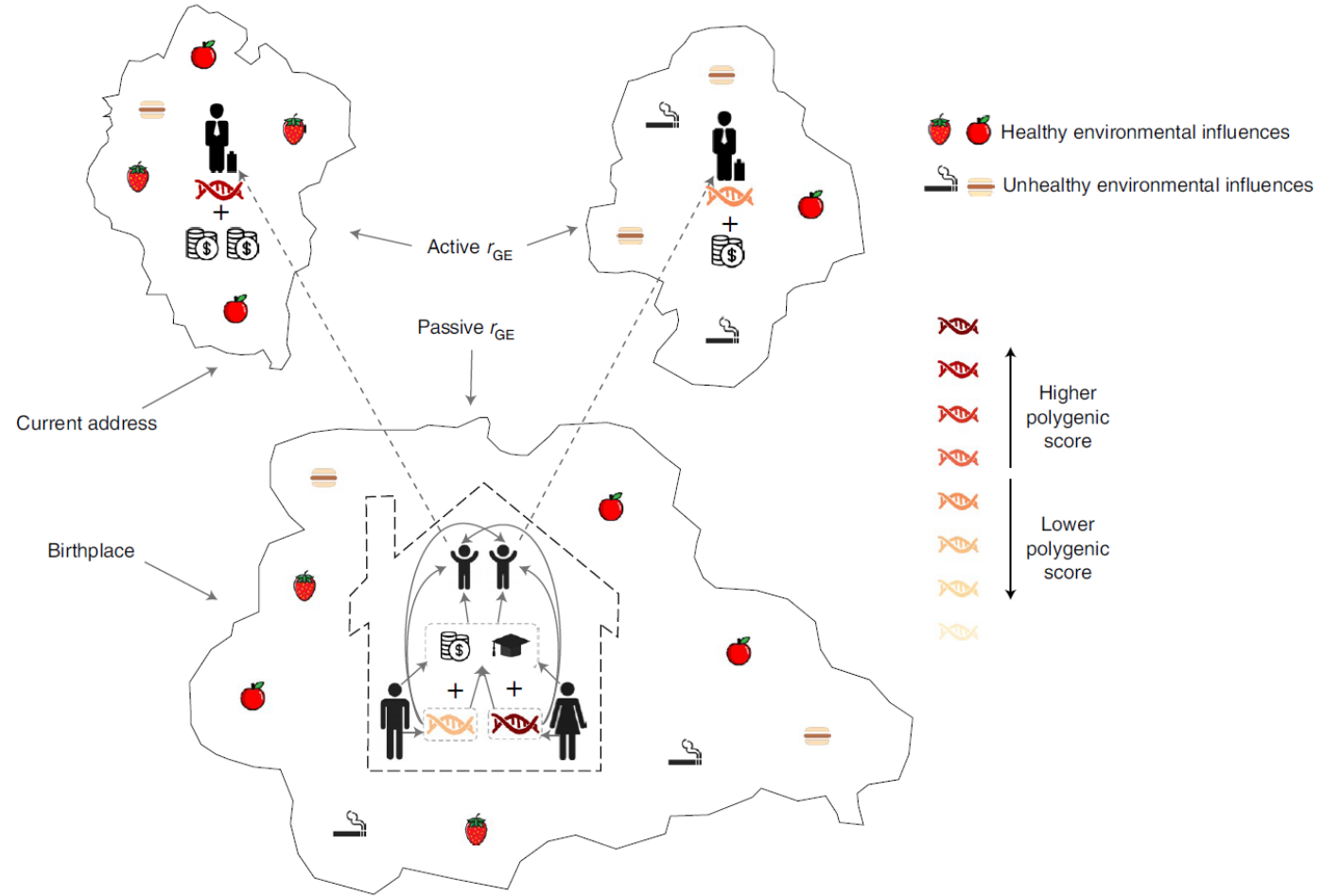
Genetic correlates of social stratification in Great Britain

Abdel Abdellaoui^{1*}, David Hugh-Jones², Loic Yengo³, Kathryn E. Kemper³, Michel G. Nivard⁴, Laura Veul¹, Yan Holtz², Brendan P. Zietsch⁵, Timothy M. Frayling⁶, Naomi R. Wray^{3,7}, Jian Yang^{3,7}, Karin J. H. Verweij¹ and Peter M. Visscher^{3,7*}

OPEN

Gene-environment correlations across geographic regions affect genome-wide association studies

Abdel Abdellaoui¹, Conor V. Dolan², Karin J. H. Verweij¹ and Michel G. Nivard²



Workshop Program

Day 1: Fundamentals

Day 2: Univariate

Day 3: Multivariate

Day 4: Gene–environment correlations

Day 5: Causality