

Copy files

- Go to Faculty\marleen\Boulder2012\Multivariate
- Copy all files to your own directory

- Go to Faculty\kees\Boulder2012\Multivariate
- Copy all files to your own directory

Introduction to Multivariate Genetic Analysis (1)

Marleen de Moor, Kees-Jan Kan & Nick Martin

Outline

- 11.00-12.30
 - Lecture Bivariate Cholesky Decomposition
 - Practical Bivariate analysis of IQ and attention problems
- 12.30-13.30 LUNCH
- 13.30-15.00
 - Lecture Multivariate Cholesky Decomposition
 - PCA versus Cholesky
 - Practical Tri- and Four-variate analysis of IQ, educational attainment and attention problems

Outline

- 11.00-12.30
 - Lecture Bivariate Cholesky Decomposition
 - Practical Bivariate analysis of IQ and attention problems
- 12.30-13.30 LUNCH
- 13.30-15.00
 - Lecture Multivariate Cholesky Decomposition
 - PCA versus Cholesky
 - Practical Tri- and Four-variate analysis of IQ, educational attainment and attention problems

Aim / Rationale multivariate models

Aim:

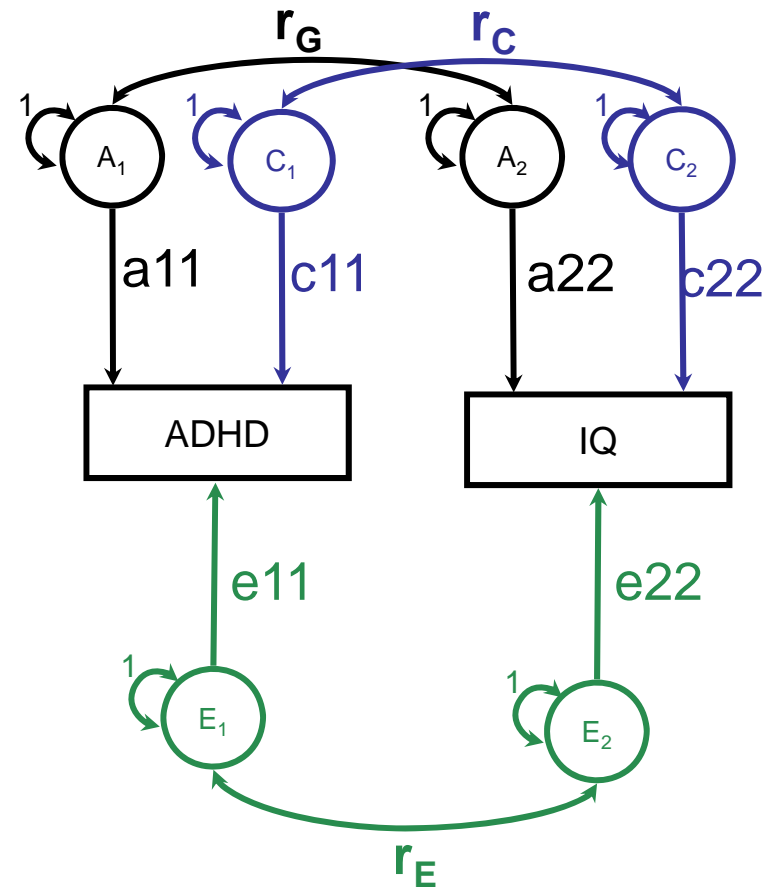
To examine the source of factors that make traits correlate or co-vary

Rationale:

- Traits may be correlated due to shared genetic factors (A or D) or shared environmental factors (C or E)
- Can use information on multiple traits from twin pairs to partition covariation into genetic and environmental components

Example

- Interested in relationship between ADHD and IQ
- How can we explain the association
 - Additive genetic factors (r_G)
 - Common environment (r_C)
 - Unique environment (r_E)

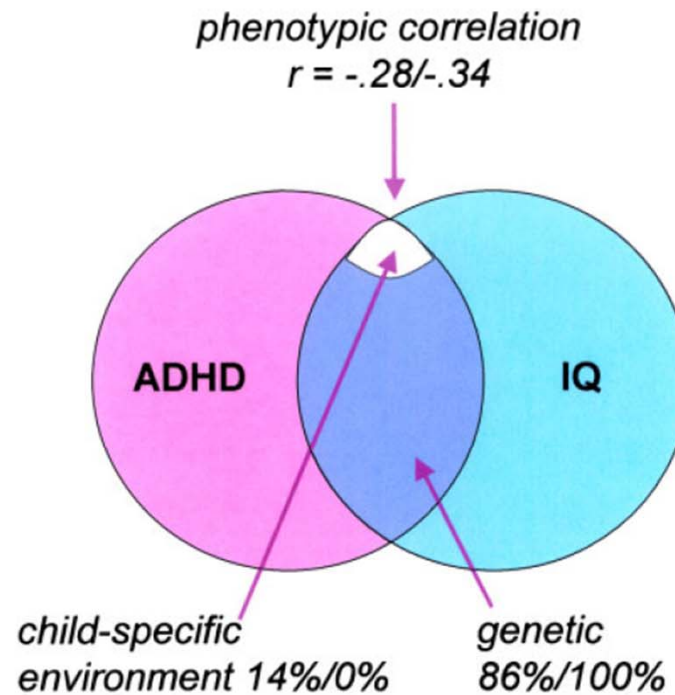


Co-Occurrence of ADHD and Low IQ Has Genetic Origins

J. Kuntsi,¹ T.C. Eley,¹ A. Taylor,¹ C. Hughes,² P. Asherson,¹ A. Caspi,¹ and T.E. Moffitt^{1*}

¹*Social, Genetic and Developmental Psychiatry Centre, Institute of Psychiatry, King's College London, London, United Kingdom*

²*Centre for Family Research, University of Cambridge, Cambridge, United Kingdom*



March 7, 2012

Fig. 1. Genetic and environmental contributions to the negative phenotypic correlation between IQ and both ADHD symptom scores and ADHD diagnosis. [Colour figure can be viewed in the online issue, which is available at www.interscience.wiley.com.]

Original articles

A longitudinal twin study on IQ, executive functioning, and attention problems during childhood and early adolescence

Tinca J. C. POLDERMAN^{1,2}, M. Florencia GOSSE^{1,3}, Danielle POSTHUMA¹, Toos C.E.M. VAN BEIJSTERVELDT¹,
Peter HEUTINK^{1,3,4}, Frank C. VERHULST² and Dorret I. BOOMSMA^{1,4}

¹Department of Biological Psychology, Vrije Universiteit Amsterdam ; ²Department of Child and Adolescent Psychiatry, Erasmus University Rotterdam ; ³Center for Neurogenomics and Cognitive Research - CNCR, Vrije Universiteit Amsterdam ; ⁴Section of Medical Genomics, Department of Clinical Genetics and Anthropogenetics, VU Medical Center, Amsterdam, The Netherlands

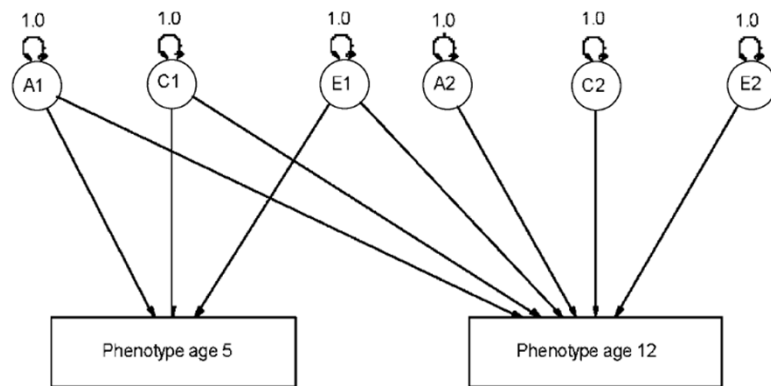


FIG. 3. — The bivariate (longitudinal) model represented for one individual

Bivariate Cholesky

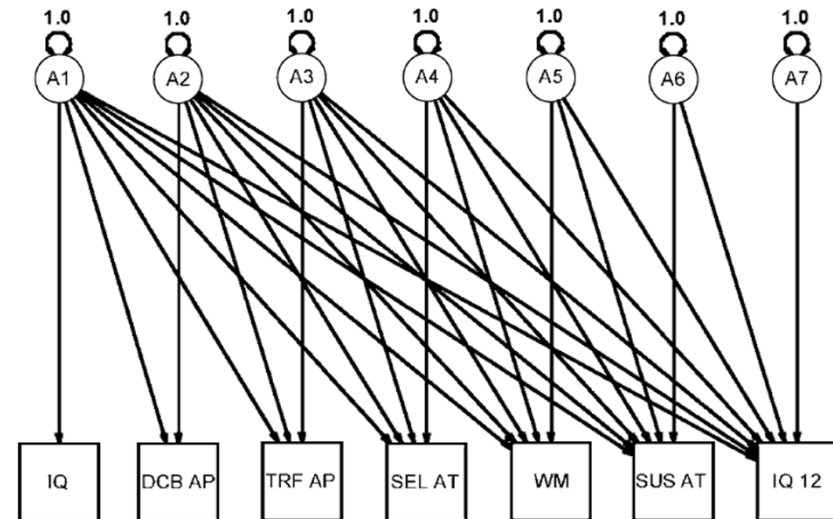


FIG. 4. — The multivariate (Cholesky) model with 7 variables represented for one individual

Multivariate Cholesky

Sources of information

- Two traits measured in twin pairs
- Interested in:
 - Cross-trait covariance *within* individuals = phenotypic covariance
 - Cross-trait covariance *between* twins = cross-trait cross-twin covariance
 - MZ:DZ ratio of cross-trait covariance *between* twins

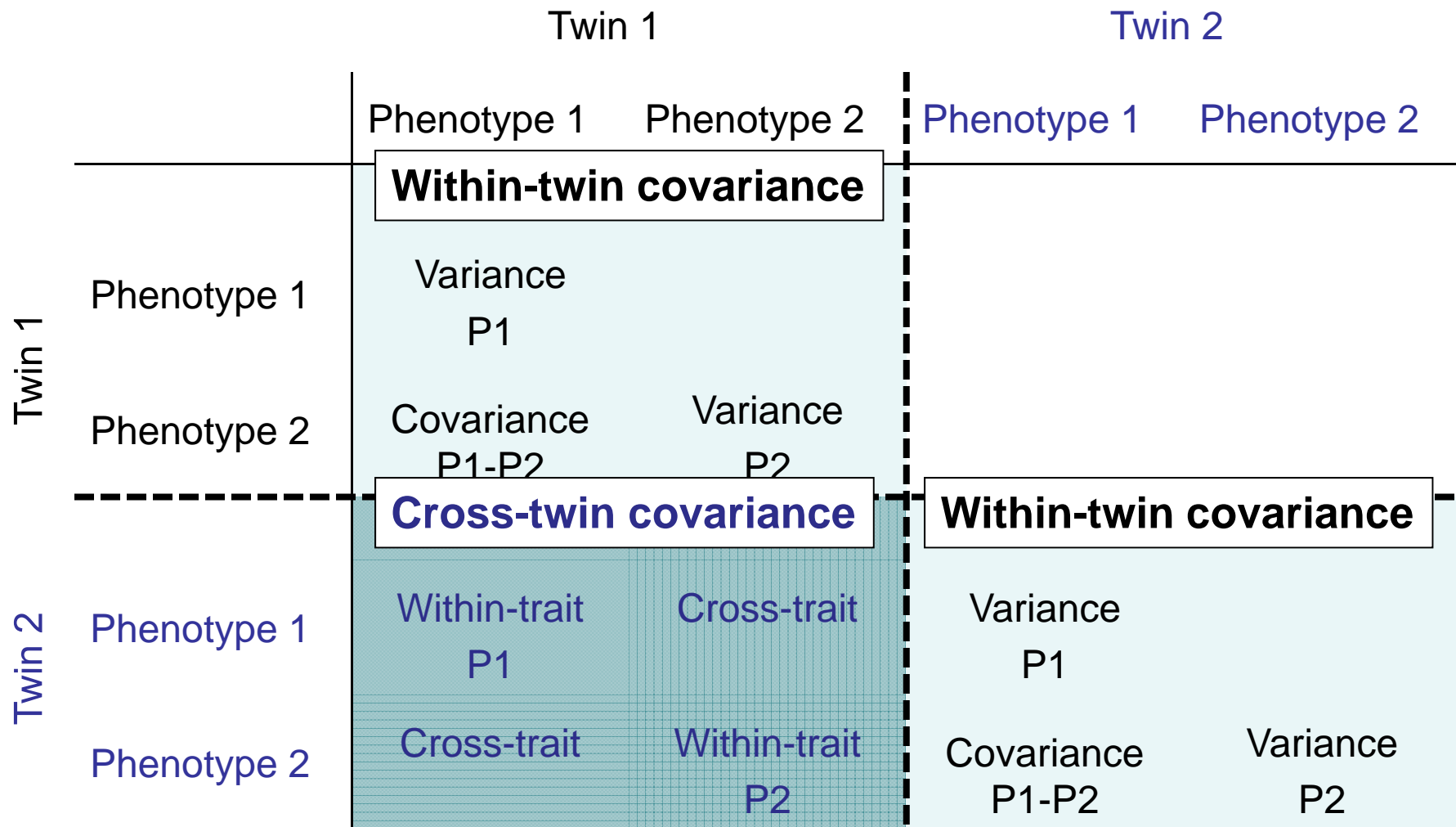
Observed Covariance Matrix: 4x4

		Twin 1		Twin 2	
		Phenotype 1	Phenotype 2	Phenotype 1	Phenotype 2
Twin 1	Phenotype 1	Variance P1			
	Phenotype 2	Covariance P1-P2	Variance P2		
Twin 2	Phenotype 1	Within-trait P1	Cross-trait	Variance P1	
	Phenotype 2	Cross-trait	Within-trait P2	Covariance P1-P2	Variance P2

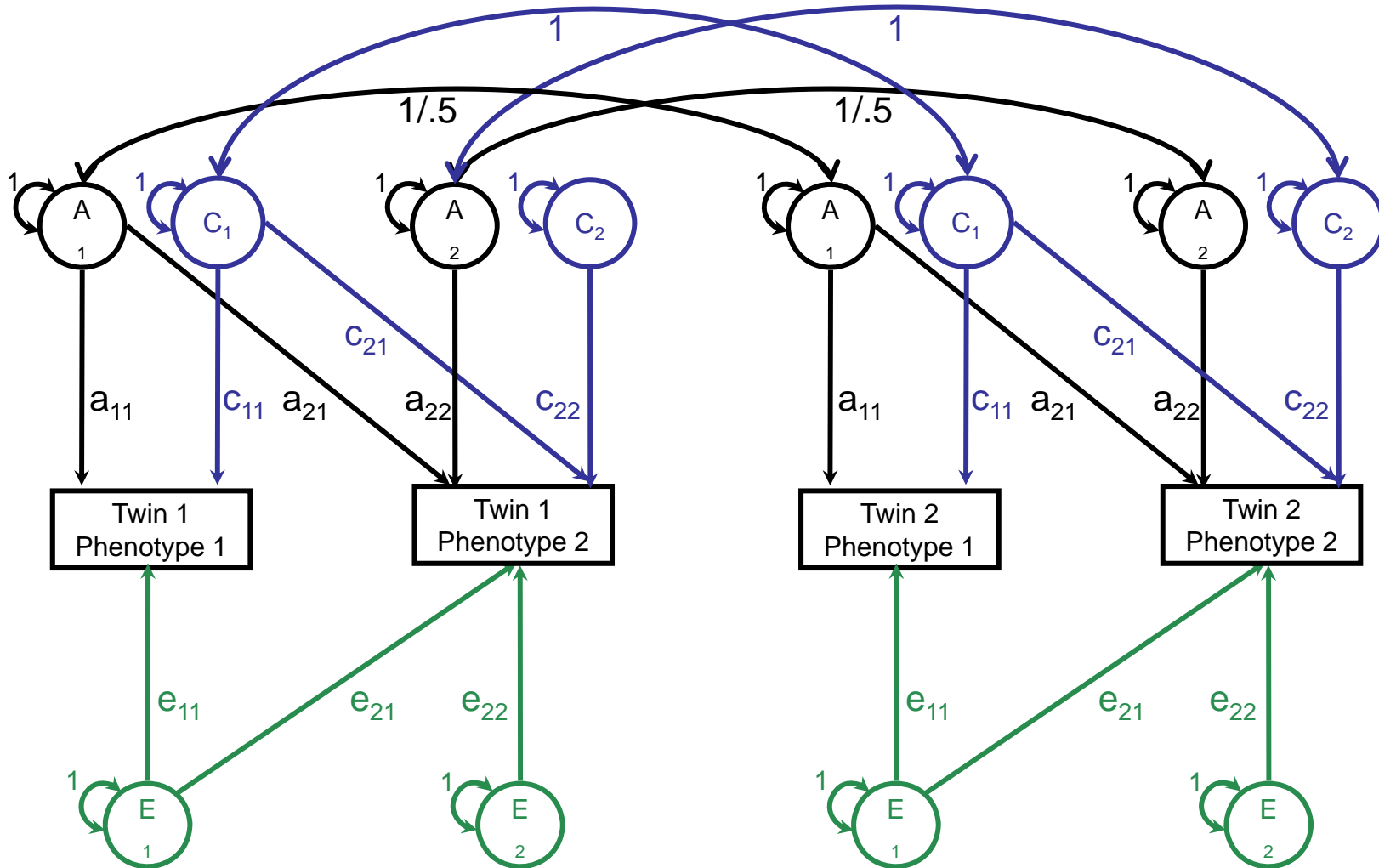
Observed Covariance Matrix: 4x4

		Twin 1		Twin 2	
		Phenotype 1	Phenotype 2	Phenotype 1	Phenotype 2
Twin 1		Within-twin covariance			
	Phenotype 1	Variance P1			
	Phenotype 2	Covariance P1-P2	Variance P2		
Twin 2				Within-twin covariance	
	Phenotype 1	Within-trait P1	Cross-trait	Variance P1	
	Phenotype 2	Cross-trait	Within-trait P2	Covariance P1-P2	Variance P2

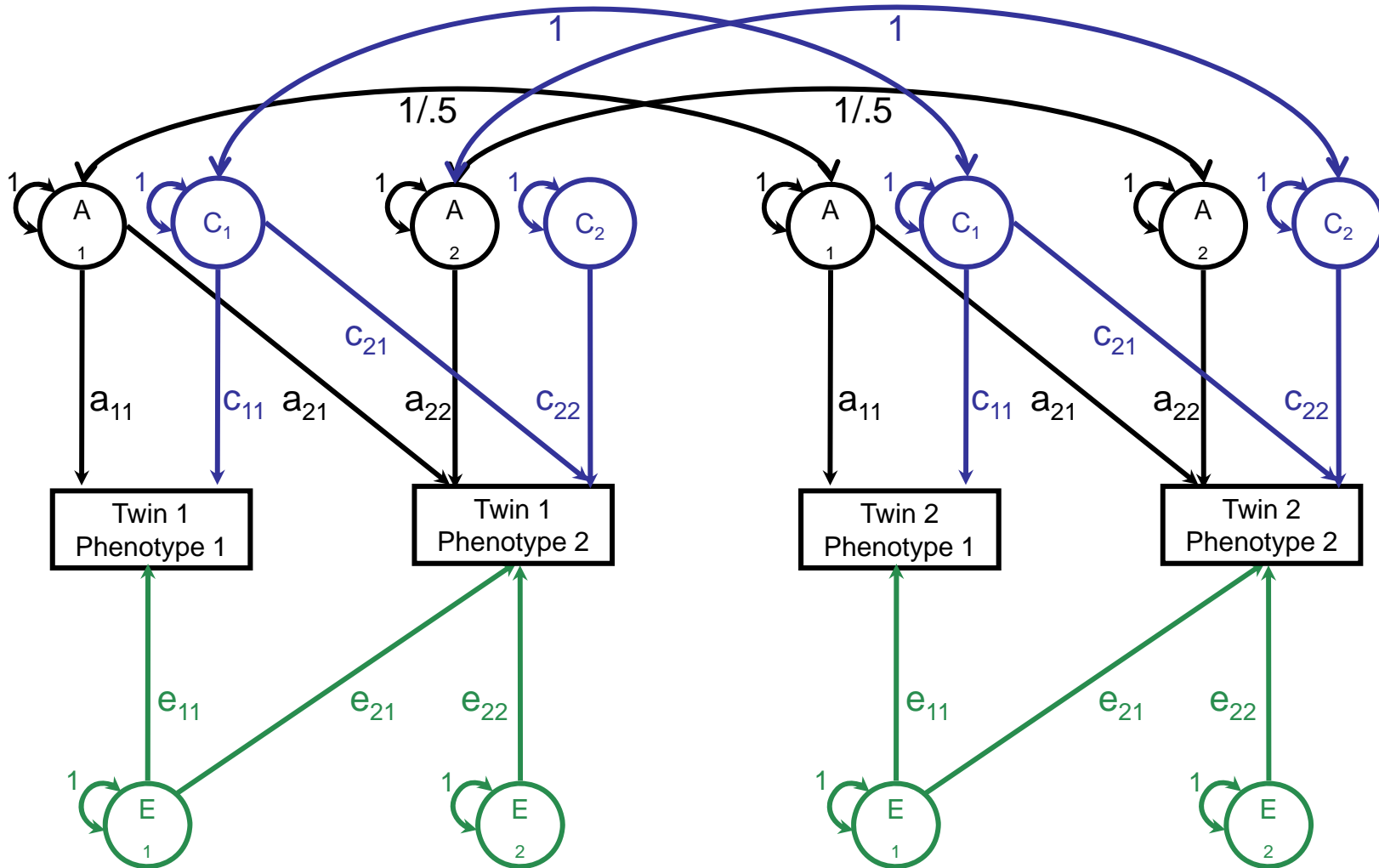
Observed Covariance Matrix: 4x4



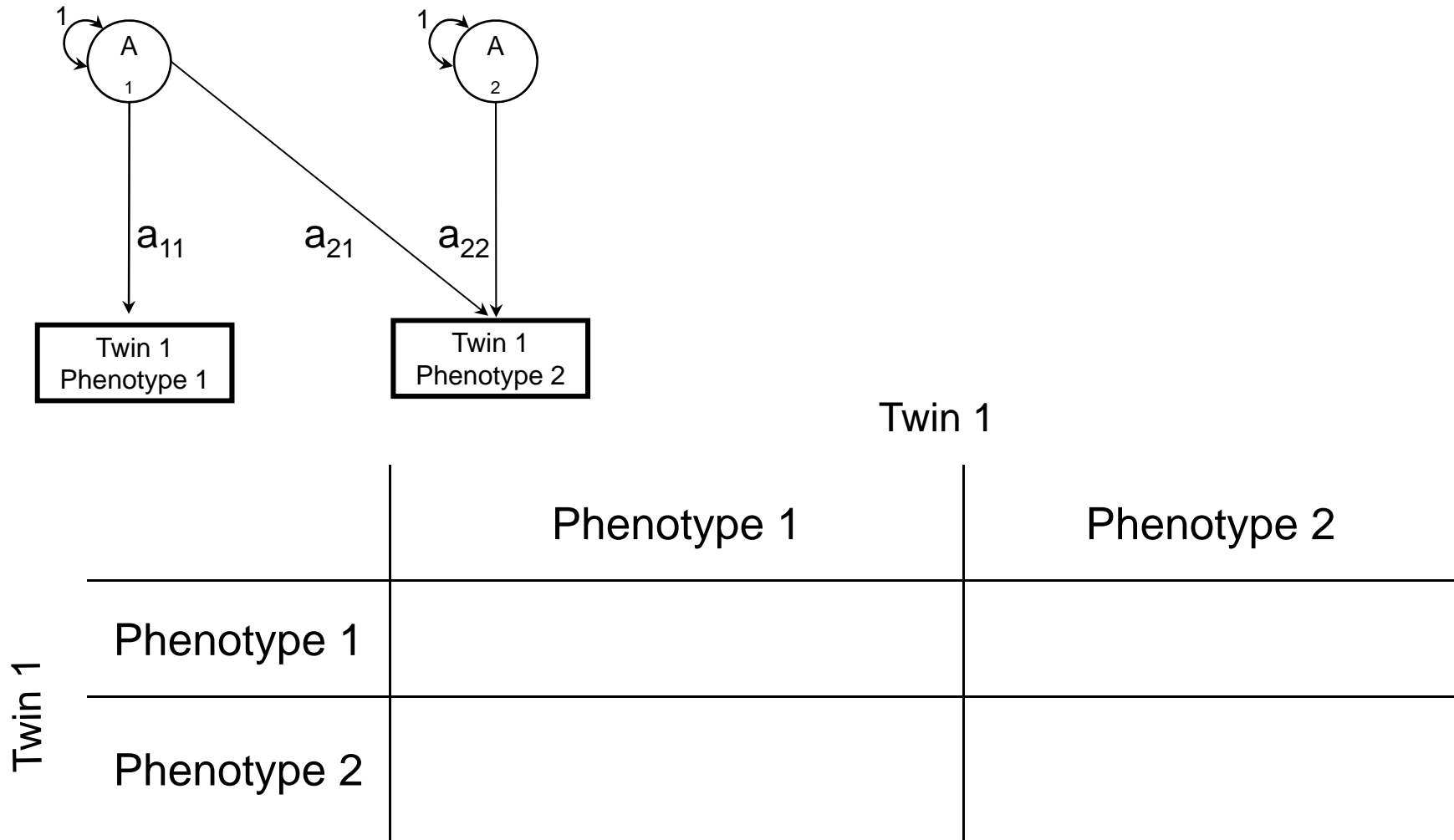
Cholesky decomposition



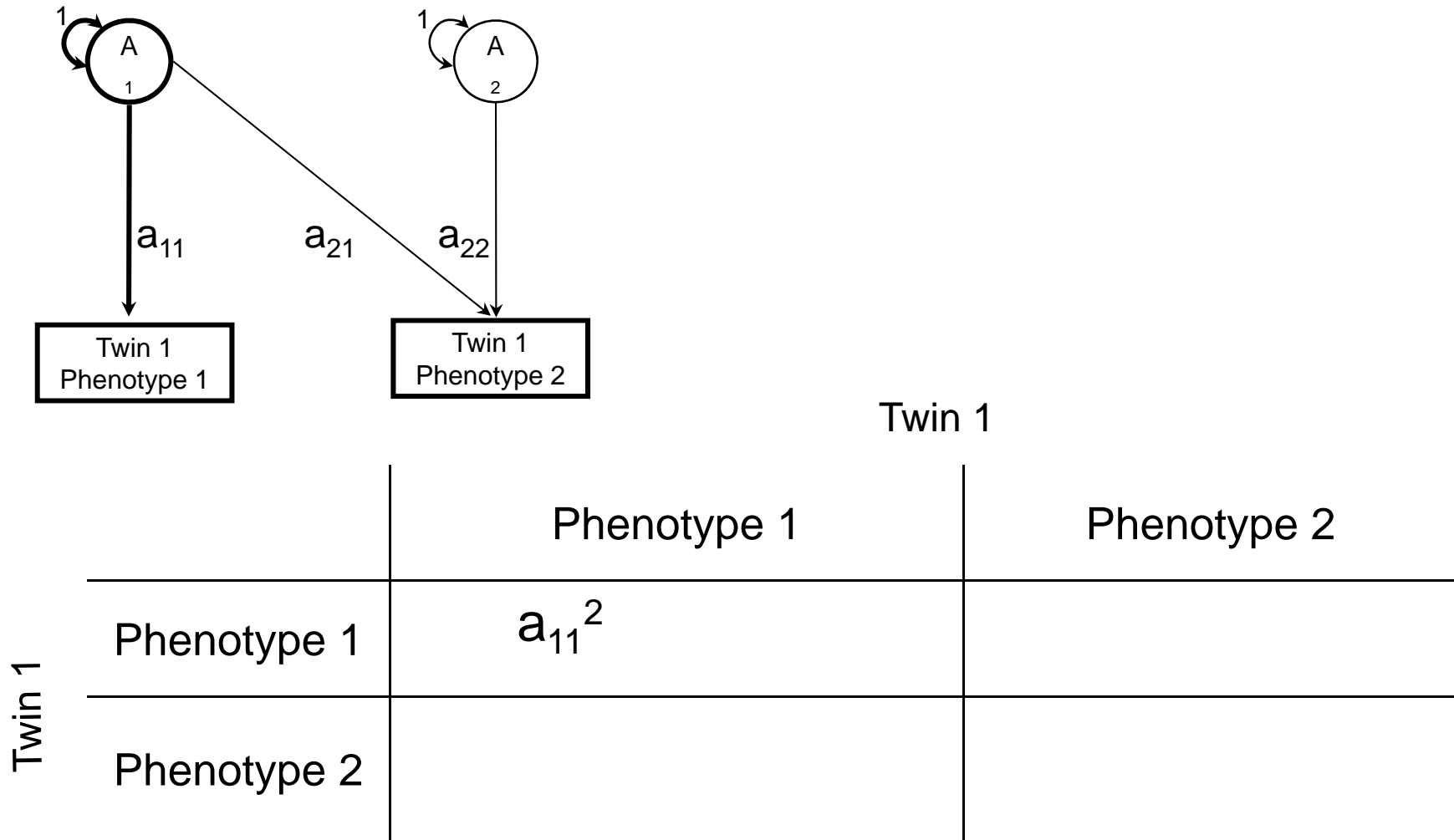
Now let's do the path tracing!



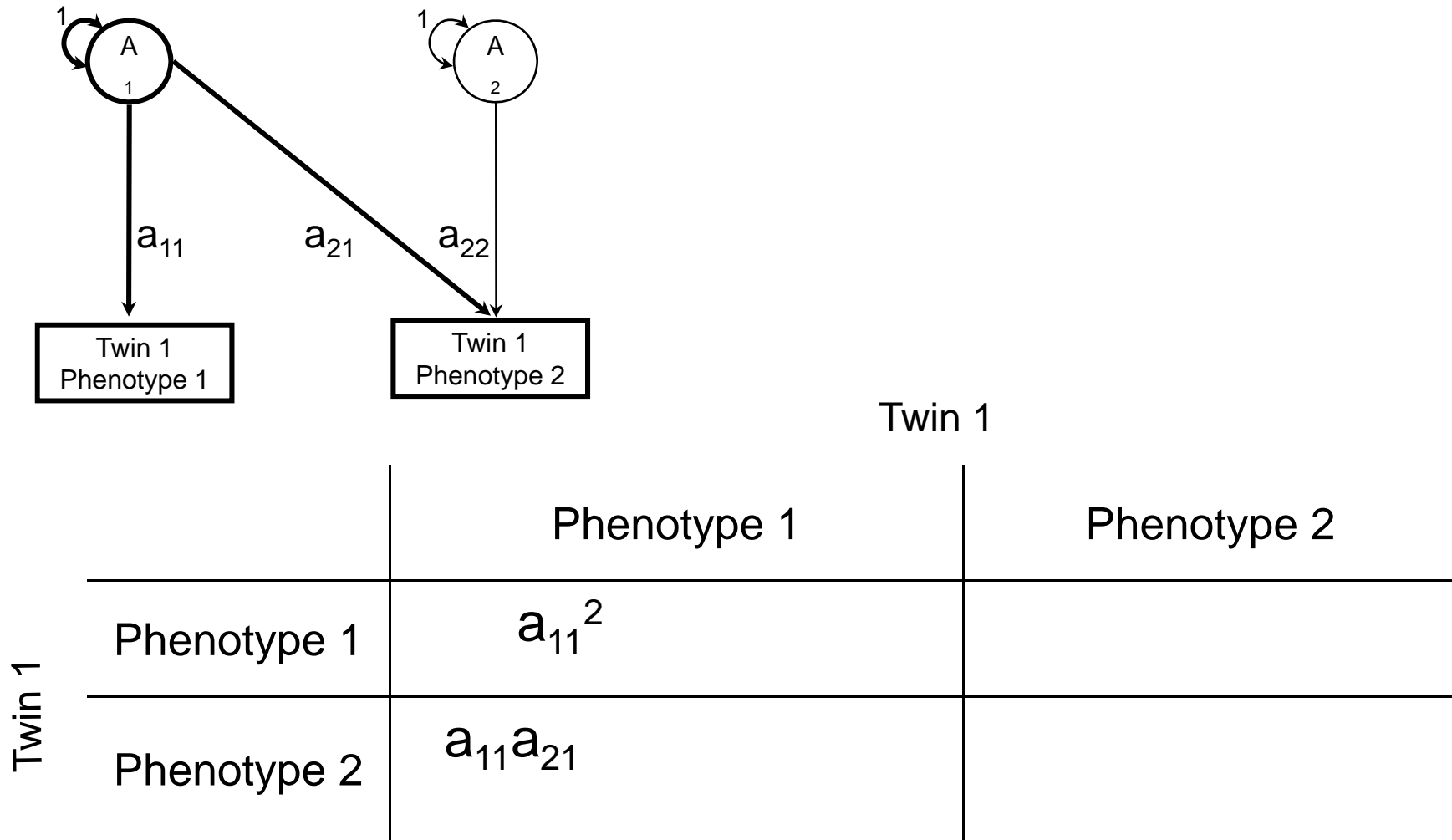
Within-Twin Covariances (A)



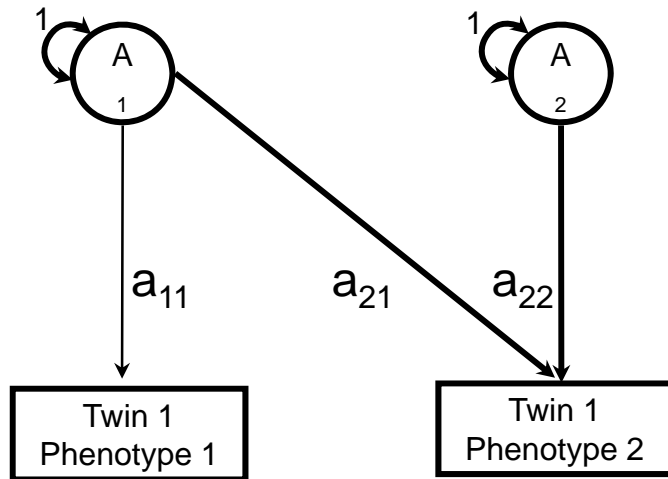
Within-Twin Covariances (A)



Within-Twin Covariances (A)

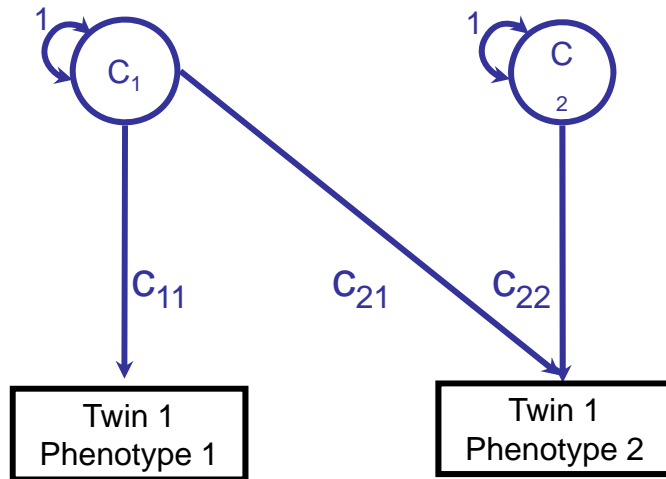


Within-Twin Covariances (A)



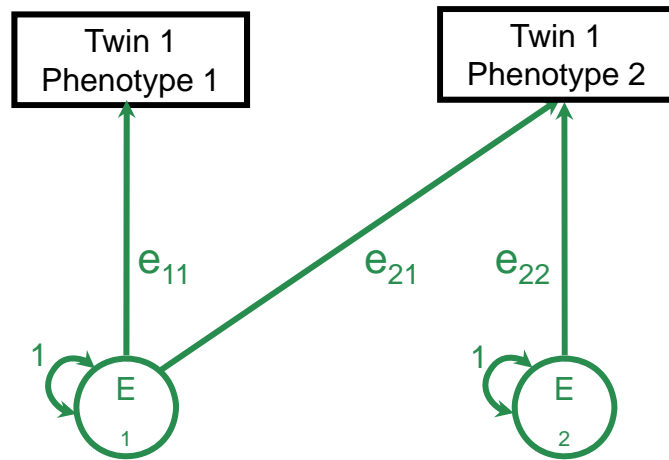
		Twin 1	
		Phenotype 1	Phenotype 2
Twin 1	Phenotype 1	a_{11}^2	
	Phenotype 2	$a_{11}a_{21}$	$a_{22}^2 + a_{21}^2$

Within-Twin Covariances (C)



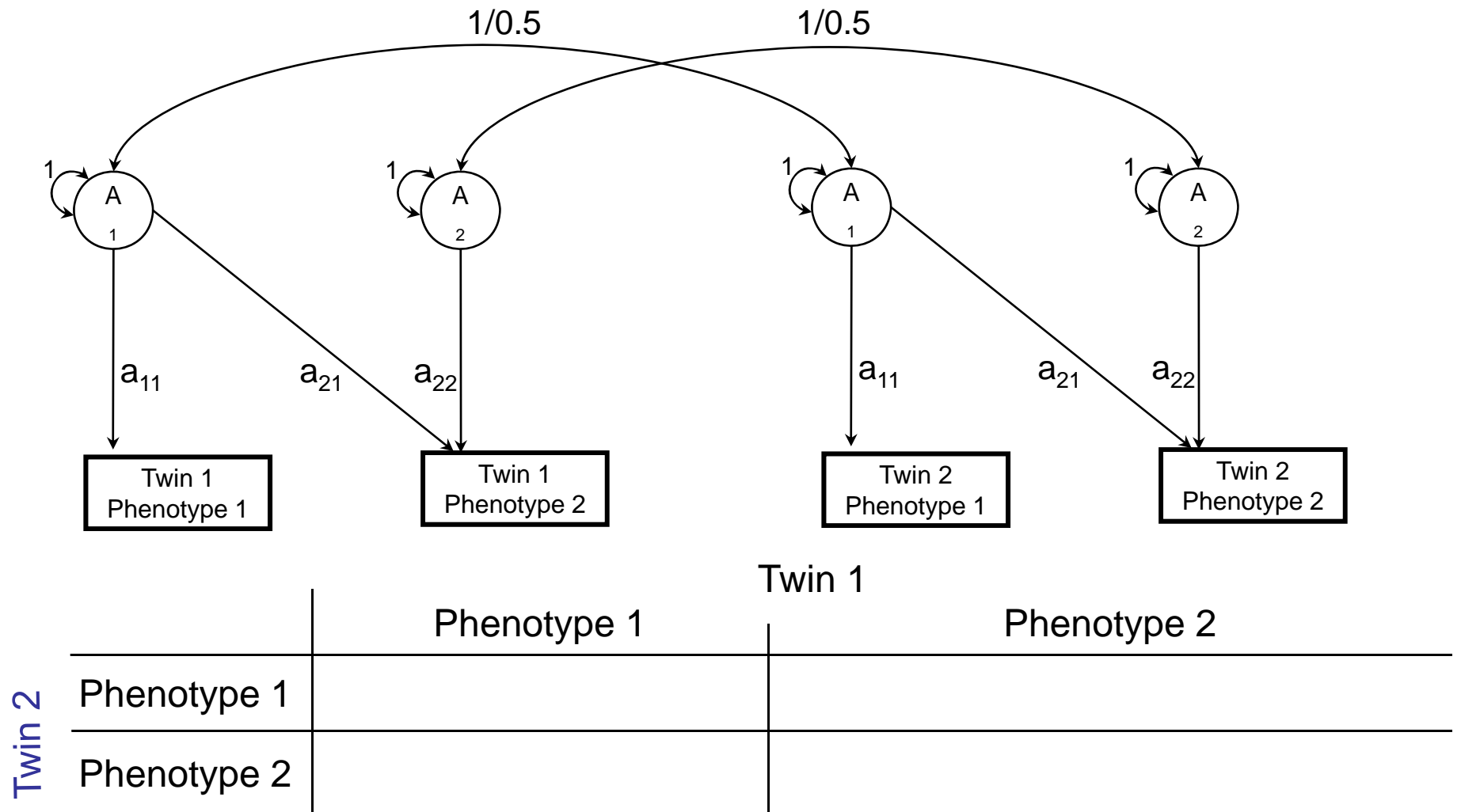
		Twin 1	
		Phenotype 1	Phenotype 2
Twin 1	Phenotype 1	$a_{11}^2 + c_{11}^2$	
	Phenotype 2	$a_{11}a_{21} + c_{11}c_{21}$	$a_{22}^2 + a_{21}^2 + c_{22}^2 + c_{21}^2$

Within-Twin Covariances (E)

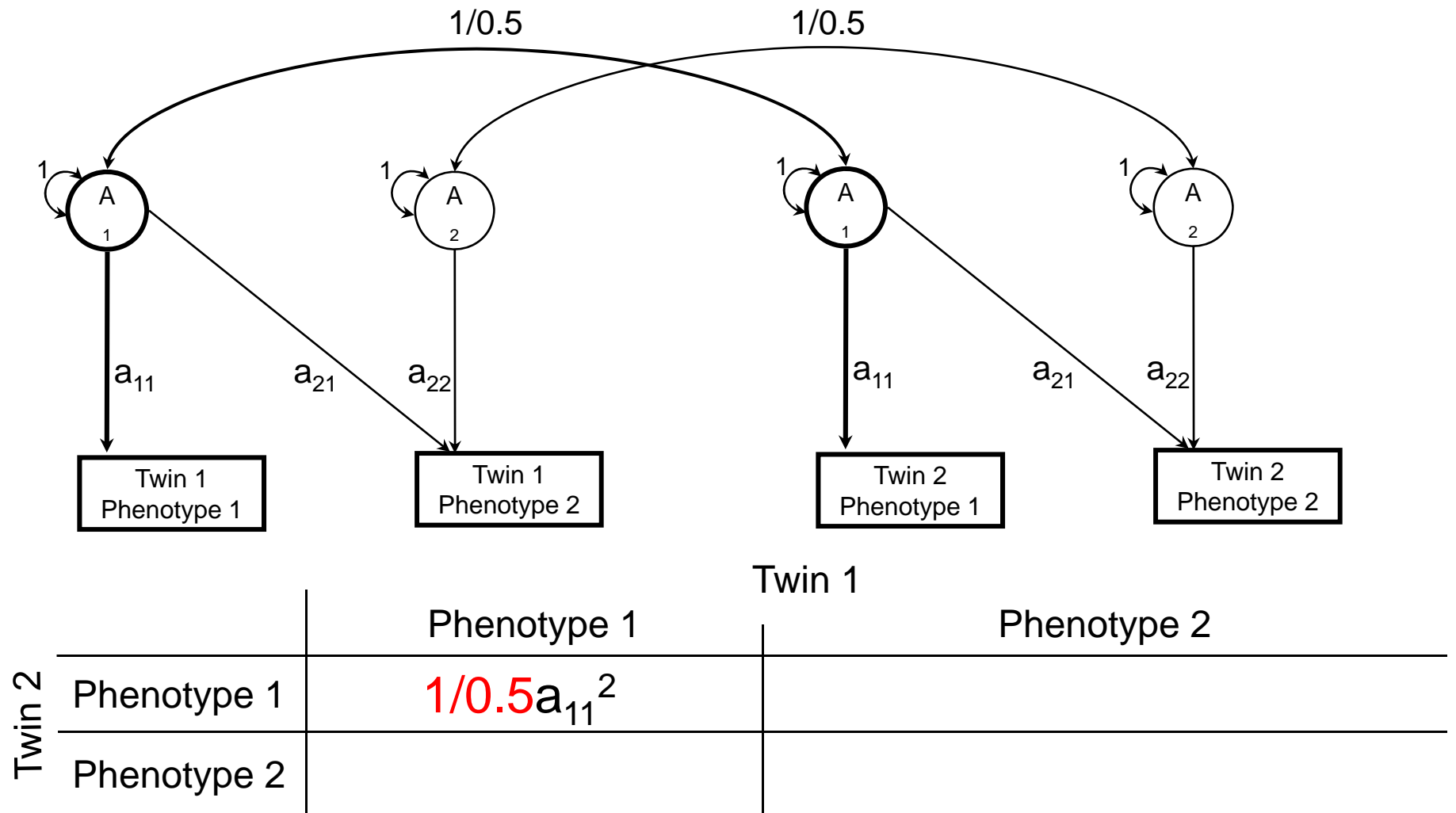


		Twin 1	
		Phenotype 1	Phenotype 2
Twin 1	Phenotype 1	$a_{11}^2 + c_{11}^2 + e_{11}^2$	
	Phenotype 2	$a_{11}a_{21} + c_{11}c_{21} + e_{11}e_{21}$	$a_{22}^2 + a_{21}^2 + c_{22}^2 + c_{21}^2 + e_{22}^2 + e_{21}^2$

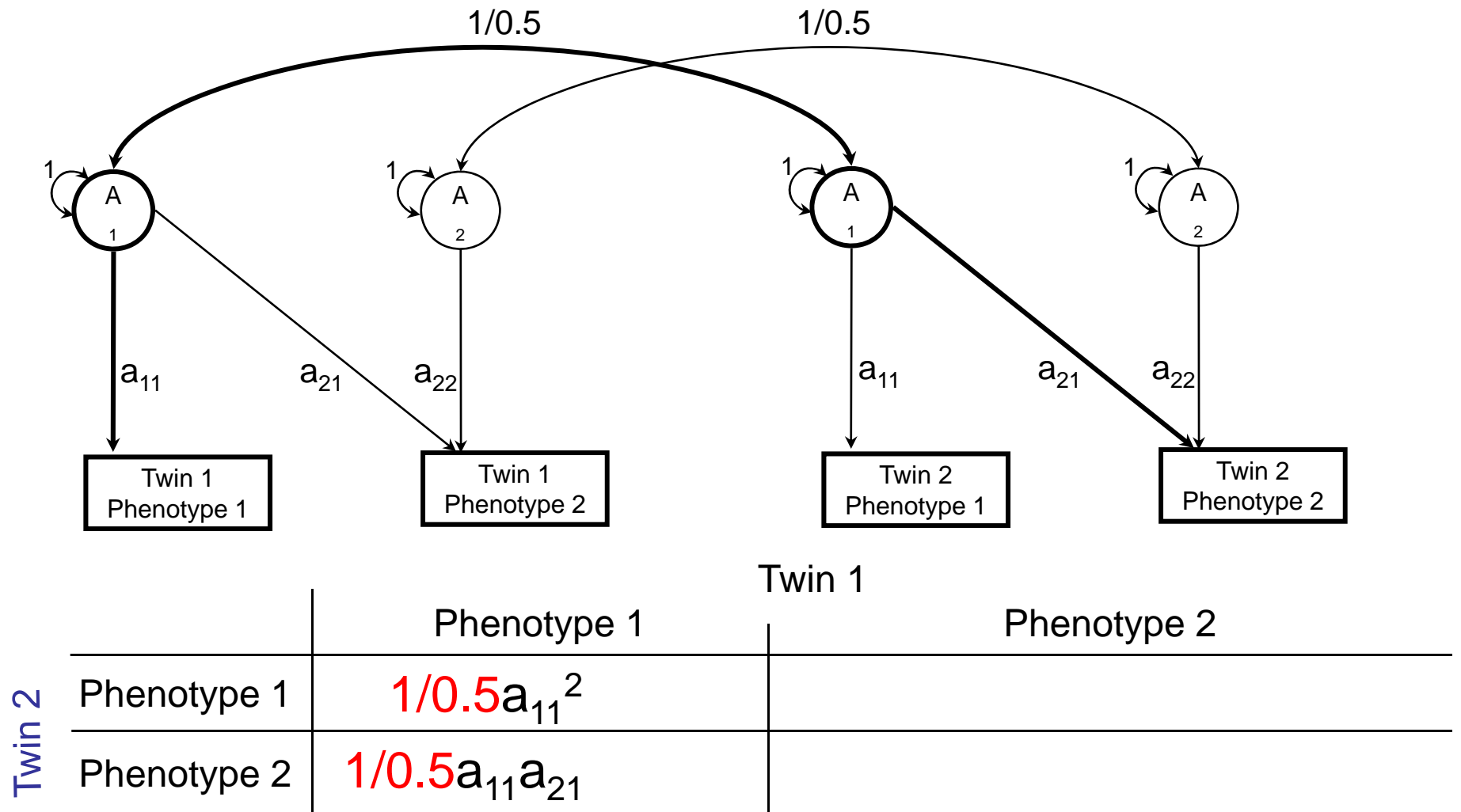
Cross-Twin Covariances (A)



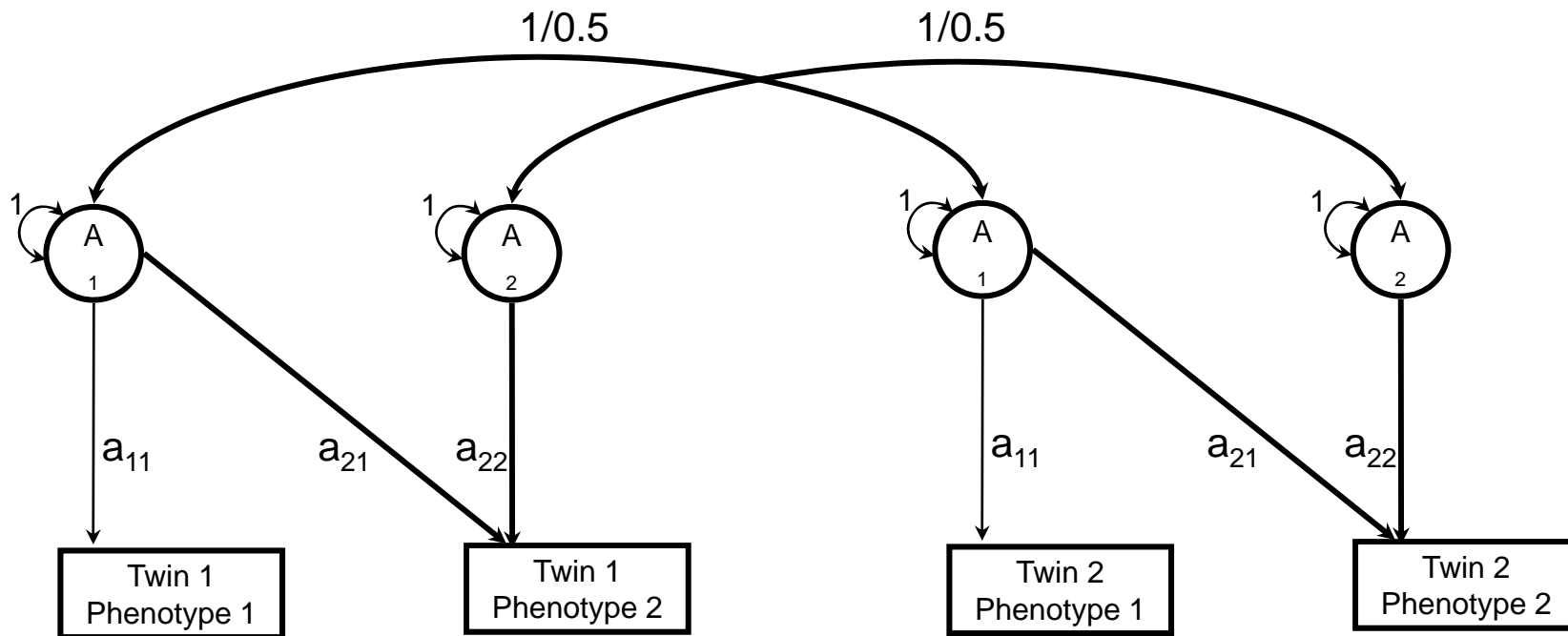
Cross-Twin Covariances (A)



Cross-Twin Covariances (A)

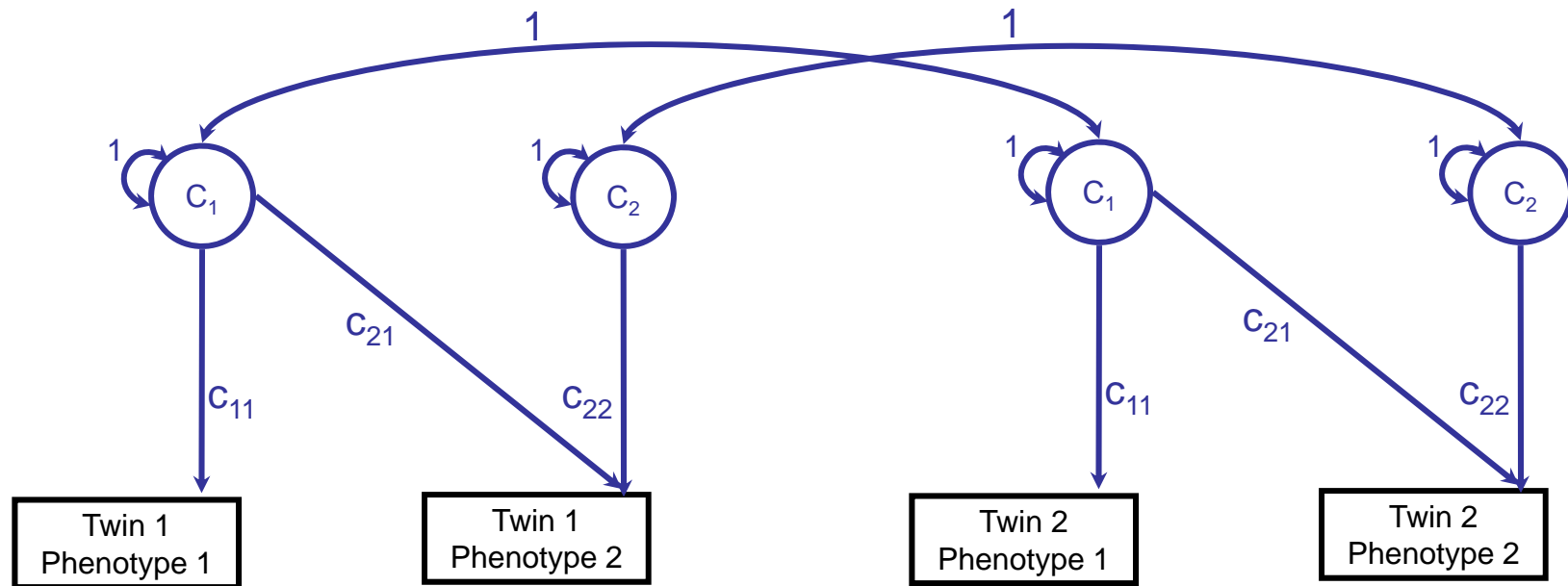


Cross-Twin Covariances (A)



		Twin 1	
		Phenotype 1	Phenotype 2
Twin 2	Phenotype 1	$1/0.5a_{11}^2$	
	Phenotype 2	$1/0.5a_{11}a_{21}$	$1/0.5a_{22}^2 + 1/0.5a_{21}^2$

Cross-Twin Covariances (C)

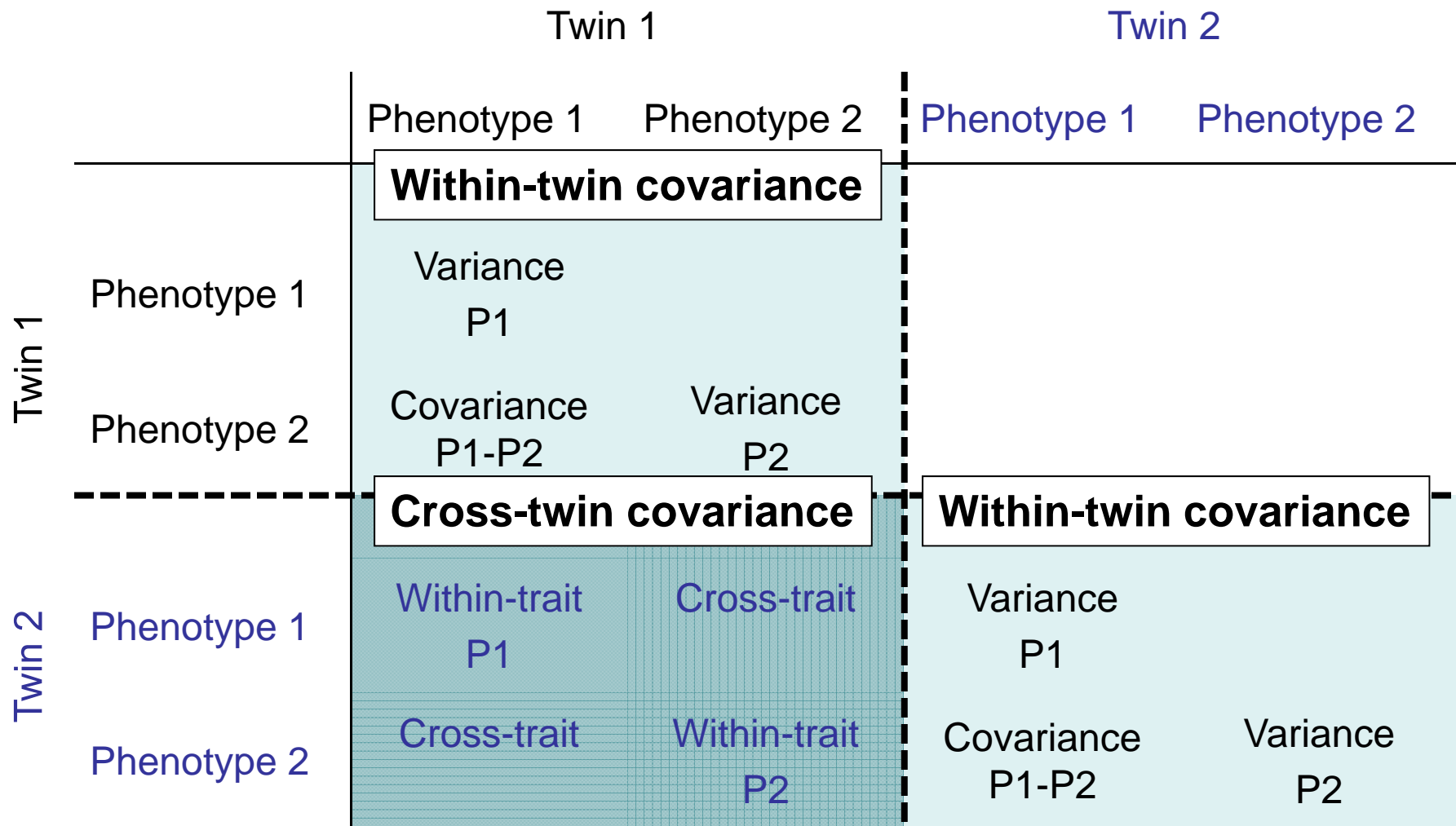


		Twin 1	
		Phenotype 1	Phenotype 2
Twin 2	Phenotype 1	$1/0.5a_{11}^2 + c_{11}^2$	
	Phenotype 2	$1/0.5a_{11}a_{21} + c_{11}c_{21}$	$1/0.5a_{22}^2 + 1/0.5a_{21}^2 + c_{22}^2 + c_{21}^2$

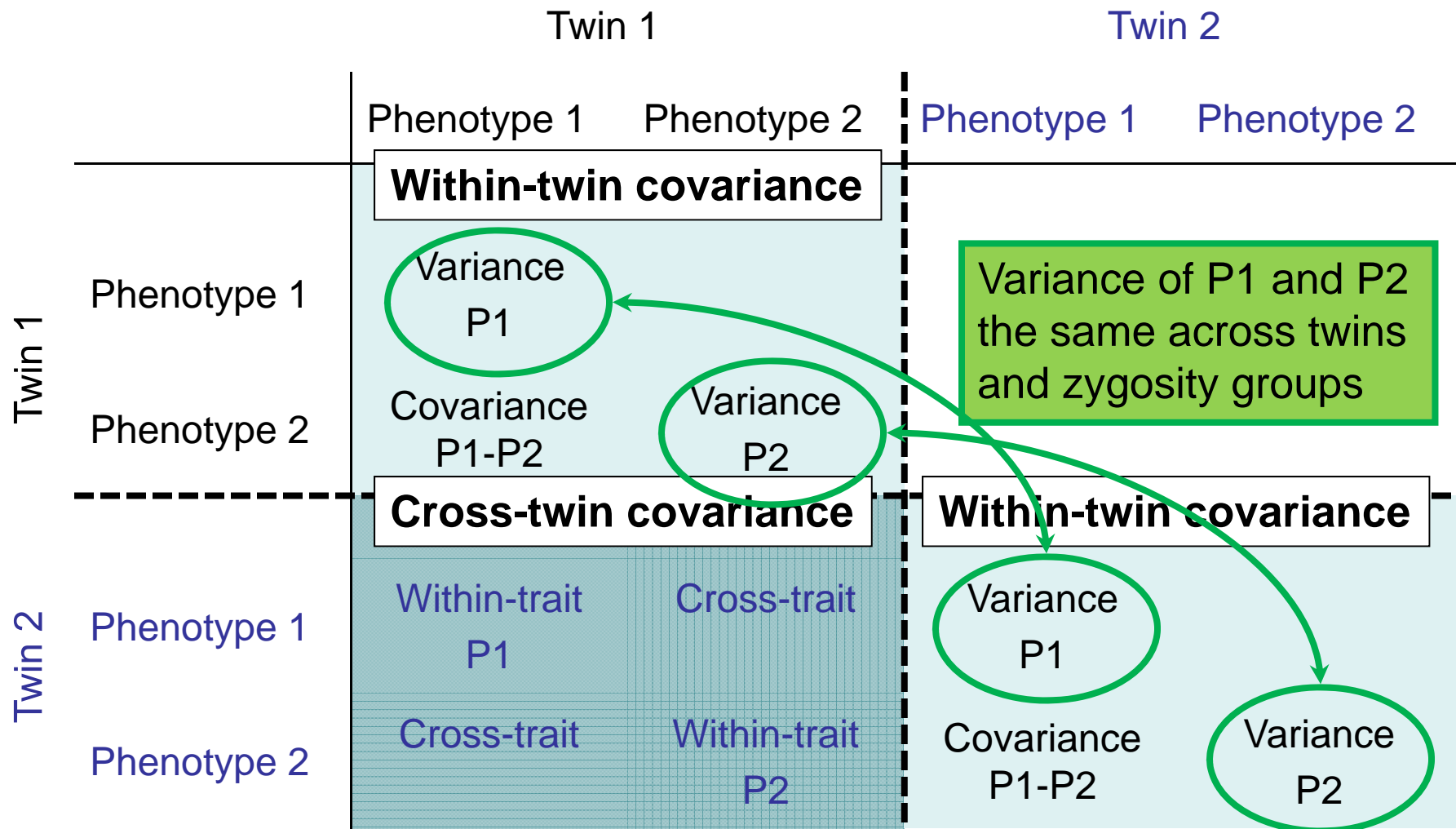
Predicted Model

		Twin 1		Twin 2	
		Phenotype 1	Phenotype 2	Phenotype 1	Phenotype 2
Twin 1		Within-twin covariance			
	Phenotype 1	$a_{11}^2 + c_{11}^2 + e_{11}^2$			
	Phenotype 2	$a_{11}a_{21} + c_{11}c_{21} + e_{11}e_{21}$	$a_{22}^2 + a_{21}^2 + c_{22}^2 + c_{21}^2 + e_{22}^2 + e_{21}^2$		
Twin 2		Cross-twin covariance		Within-twin covariance	
	Phenotype 1	$1/5 a_{11}^2 + c_{11}^2$		$a_{11}^2 + c_{11}^2 + e_{11}^2$	
	Phenotype 2	$1/5 a_{11}a_{21} + c_{11}c_{21}$	$1/5 a_{22}^2 + 1/5 a_{21}^2 + c_{22}^2 + c_{21}^2$	$a_{11}a_{21} + c_{11}c_{21} + e_{11}e_{21}$	$a_{22}^2 + a_{21}^2 + c_{22}^2 + c_{21}^2 + e_{22}^2 + e_{21}^2$

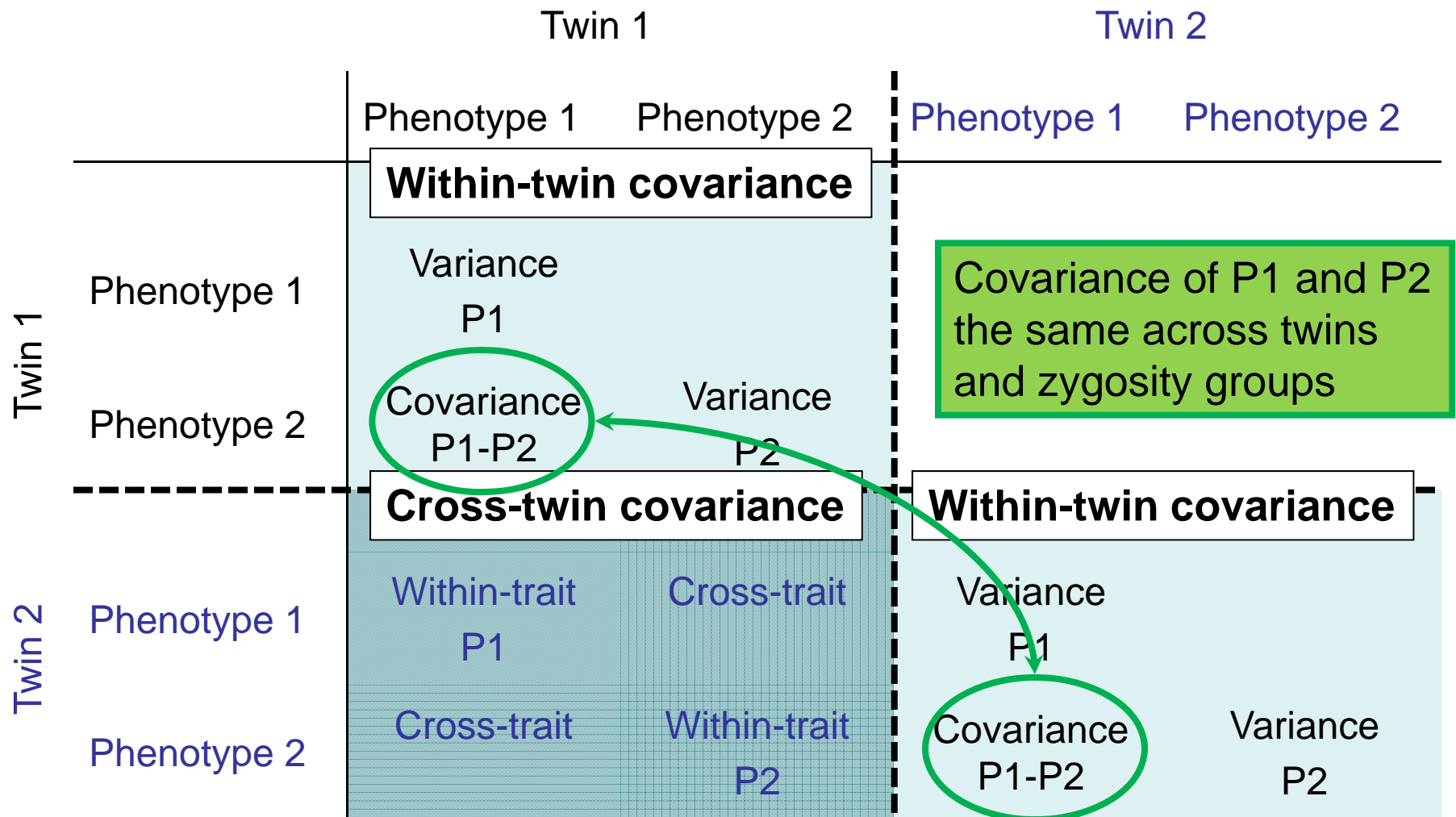
Predicted Model



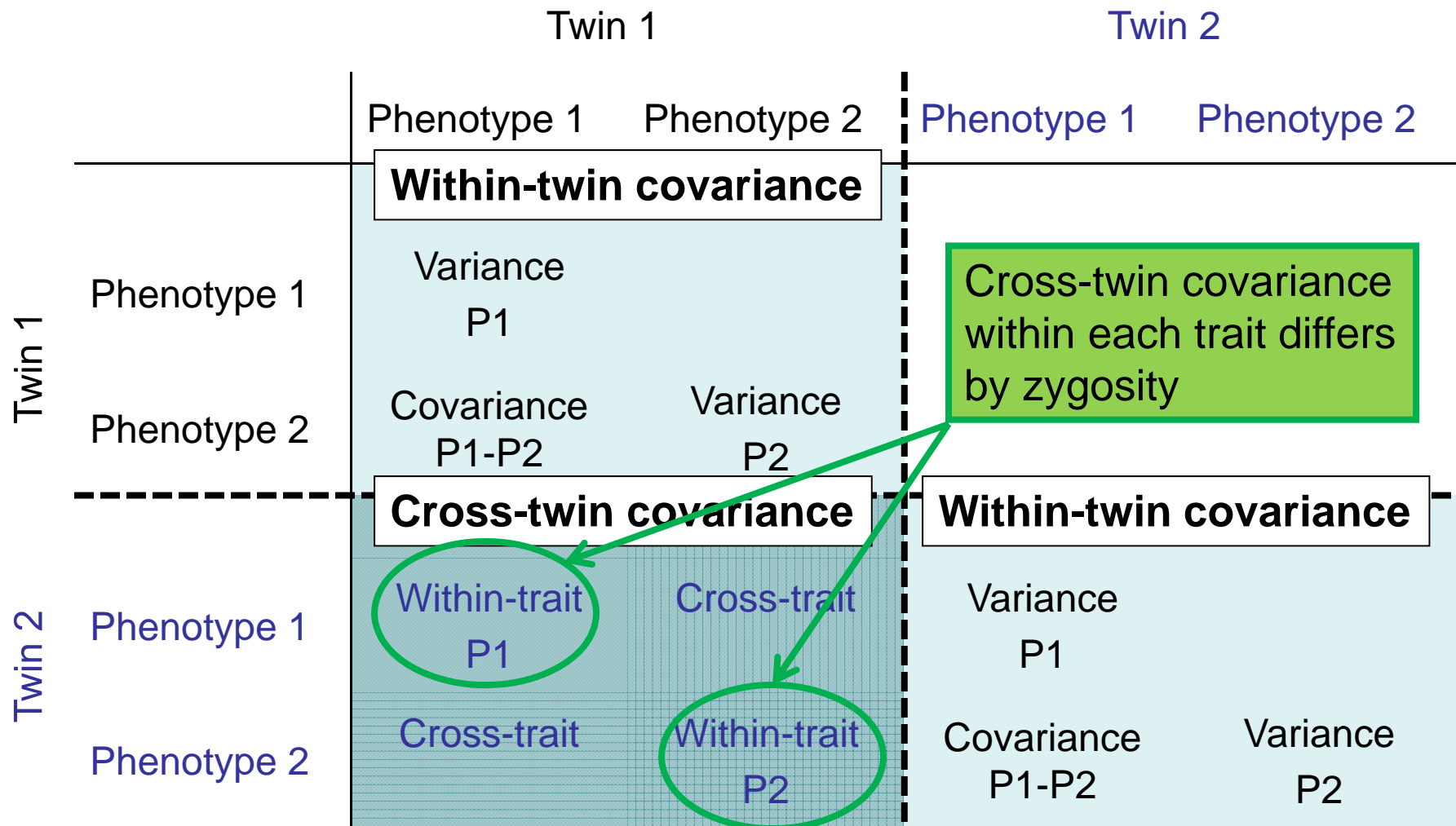
Predicted Model



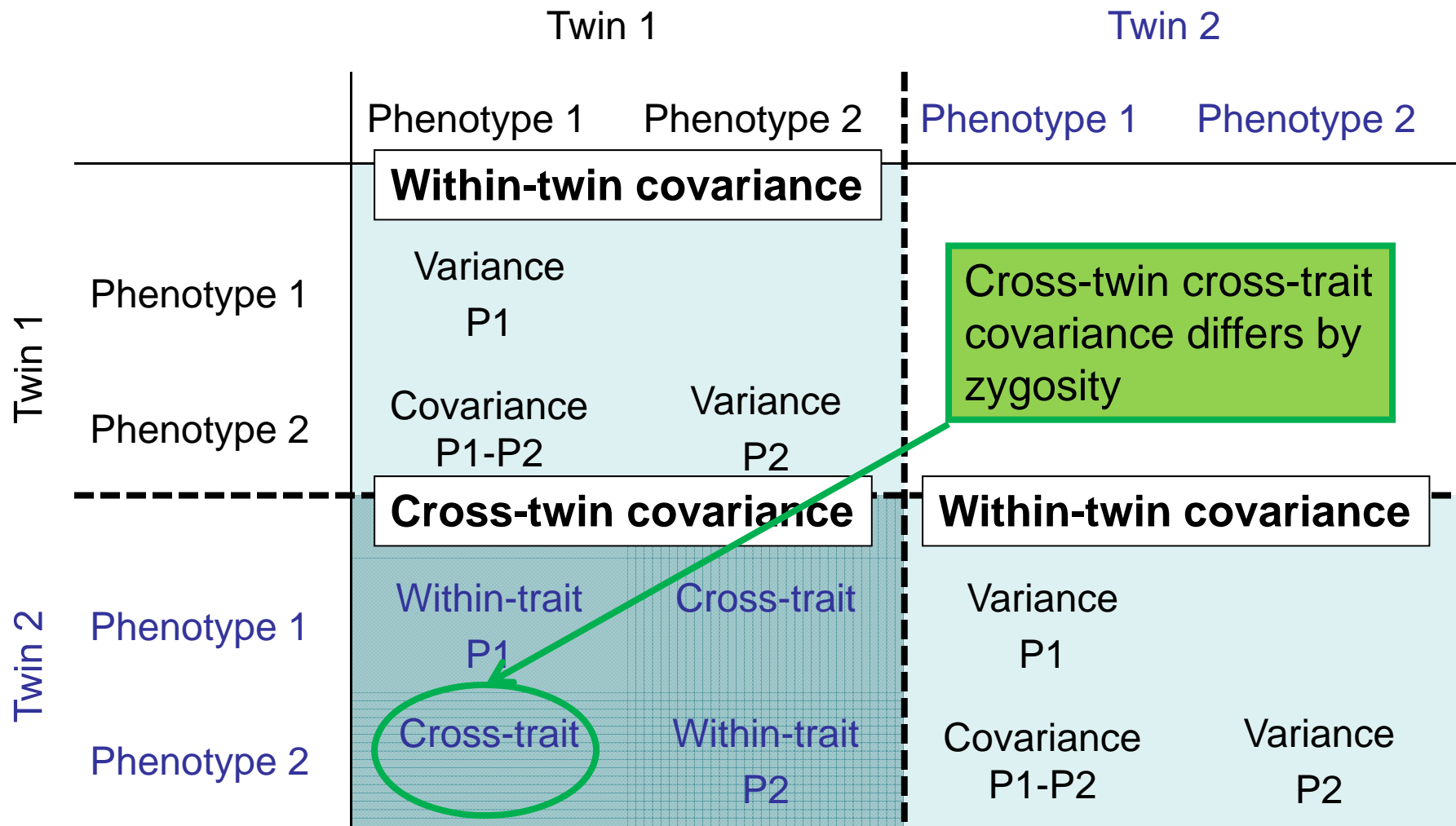
Predicted Model



Predicted Model



Predicted Model



Example covariance matrix MZ

		Twin 1		Twin 2	
		ADHD	IQ	ADHD	IQ
Twin 1	ADHD	1			
	IQ	-0.26	1		
Twin 2	ADHD	0.64	-0.21	1	
	IQ	-0.25	0.70	-0.31	1

Within-twin covariance (Twin 1)

Cross-twin covariance (Twin 1 to Twin 2)

Within-twin covariance (Twin 2)

Example covariance matrix DZ

		Twin 1		Twin 2	
		ADHD	IQ	ADHD	IQ
Twin 1	ADHD	1			
	IQ	-0.31	1		
Twin 2	ADHD	0.20	-0.12	1	
	IQ	-0.12	0.53	-0.27	1

Within-twin covariance (Twin 1)

Cross-twin covariance (Twin 1 to Twin 2)

Within-twin covariance (Twin 2)

Kuntsi et al. study

44 Kuntsi et al.

TABLE IA. Within-Pair Pearson Correlations: ADHD Symptom Scores and IQ

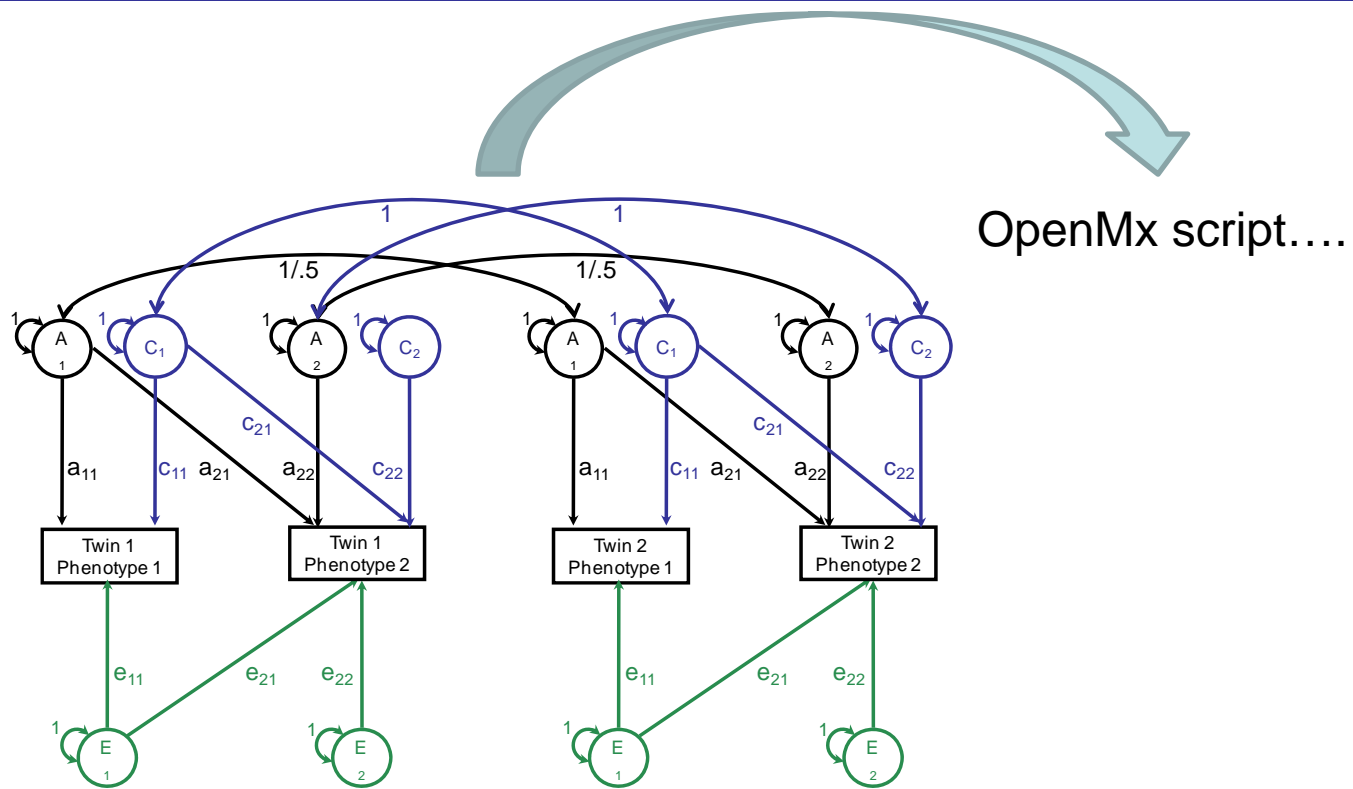
	Twin 1 ADHD symptoms	Twin 1 IQ	Twin 2 ADHD symptoms	Twin 2 IQ
MZ twins				
Twin 1 ADHD symptoms	1.00			
Twin 1 IQ	-0.26	1.00		
Twin 2 ADHD symptoms	0.64	-0.21	1.00	
Twin 2 IQ	-0.25	0.70	-0.31	1.00
Mean (SD)	15.46 (11.52) ^a	96.81 (13.64)	14.99 (11.12) ^a	97.15 (14.32)
DZ twins				
Twin 1 ADHD symptoms	1.00			
Twin 1 IQ	-0.31	1.00		
Twin 2 ADHD symptoms	0.20	-0.12	1.00	
Twin 2 IQ	-0.12	0.53	-0.27	1.00
Mean (SD)	16.93 (11.86) ^a	98.88 (14.61)	14.30 (11.00) ^a	98.44 (15.07)

^aPrior to transformation.

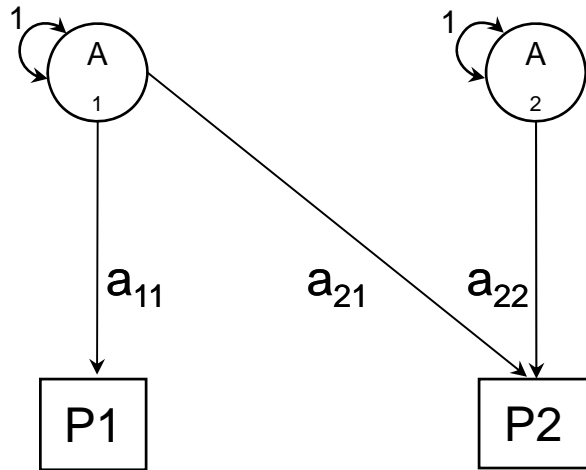
Summary

- Within-twin cross-trait covariance (phenotypic covariance) implies common aetiological influences
- Cross-twin cross-trait covariances >0 implies common aetiological influences are familial
- Whether familial influences are genetic or common environmental is shown by MZ:DZ ratio of cross-twin cross-trait covariances

Specification in OpenMx?



Within-Twin Covariance (A)



Path Tracing:

$$\Sigma_A = \begin{bmatrix} a_{11}^2 & a_{11}a_{21} \\ a_{21}a_{11} & a_{21}^2 + a_{22}^2 \end{bmatrix}$$

Lower 2 x 2 matrix:

$$\begin{matrix} & a_1 & a_2 \\ \text{P1} & \blacksquare & 0 \\ \text{P2} & a_{21} & a_{22} \end{matrix}$$

$$\Sigma_A = a * a^T$$

$$\Sigma_A = a \% * \% t(a)$$

$$= \begin{bmatrix} \blacksquare & 0 \\ a_{21} & a_{22} \end{bmatrix} * \begin{bmatrix} \blacksquare & a_{21} \\ 0 & a_{22} \end{bmatrix}$$

$$= \begin{bmatrix} a_{11}^2 + 0 \times 0 & a_{11}a_{21} + 0 \times a_{22} \\ a_{21}a_{11} + 0 \times a_{22} & a_{21}^2 + a_{22}^2 \end{bmatrix}$$

Within-Twin Covariance (A)

$$\begin{aligned}\Sigma_A &= a * a^T \\ \Sigma_A &= a \% * \% t(a) \\ &= \begin{bmatrix} \blacksquare & 0 \\ a_{21} & a_{22} \end{bmatrix} * \begin{bmatrix} \blacksquare & a_{21} \\ 0 & a_{22} \end{bmatrix} \\ &= \begin{bmatrix} a_{11}^2 + 0 \times 0 & a_{11}a_{21} + 0 \times a_{22} \\ a_{21}a_{11} + 0 \times a_{22} & a_{21}^2 + a_{22}^2 \end{bmatrix}\end{aligned}$$

OpenMx

```
Vars <- c("FSIQ", "AttProb")  
nv <- length(Vars)  
aLabs <- c("a11", "a21", "a22")
```

```
pathA <- mxMatrix(name = "a", type = "Lower", nrow = nv, ncol = nv, labels = aLabs)  
covA <- mxAlgebra(name = "A", expression = a %*% t(a))
```

Within-Twin Covariance (A+C+E)

$$\Sigma_A = a \% \% t(a)$$

$$\Sigma_C = c \% \% t(c) = \begin{bmatrix} c_{11}^2 & c_{11}c_{21} \\ c_{21}c_{11} & c_{21}^2 + c_{22}^2 \end{bmatrix}$$

$$\Sigma_E = e \% \% t(e) = \begin{bmatrix} e_{11}^2 & e_{11}e_{21} \\ e_{21}e_{11} & e_{21}^2 + e_{22}^2 \end{bmatrix}$$

Using matrix addition, the total within-twin covariance for the phenotypes is defined as:

$$\Sigma_V = \square + \Sigma_C + \Sigma_E$$

$$\Sigma_V = \begin{bmatrix} \square + c_{11}^2 + e_{11}^2 & \square + c_{11}c_{21} + e_{11}e_{21} \\ \square + c_{21}c_{11} + e_{11}e_{21} & \square + c_{21}^2 + c_{22}^2 + e_{21}^2 + e_{22}^2 \end{bmatrix}$$

OpenMx Matrices & Algebra

OpenMx

OpenMx

```
Vars <- c("FSIQ", "AttProb")  
nv <- length(Vars)
```

```
aLabs <- c("a11", "a21", "a22")  
cLabs <- c("c11", "c21", "c22")  
eLabs <- c("e11", "e21", "e22")
```

```
# Matrices a, c, and e to store a, c, and e Path Coefficients
```

```
pathA <- mxMatrix(name = "a", type = "Lower", nrow = nv, ncol = nv, labels = aLabs)  
pathC <- mxMatrix(name = "c", type = "Lower", nrow = nv, ncol = nv, labels = cLabs)  
pathE <- mxMatrix(name = "e", type = "Lower", nrow = nv, ncol = nv, labels = eLabs)
```

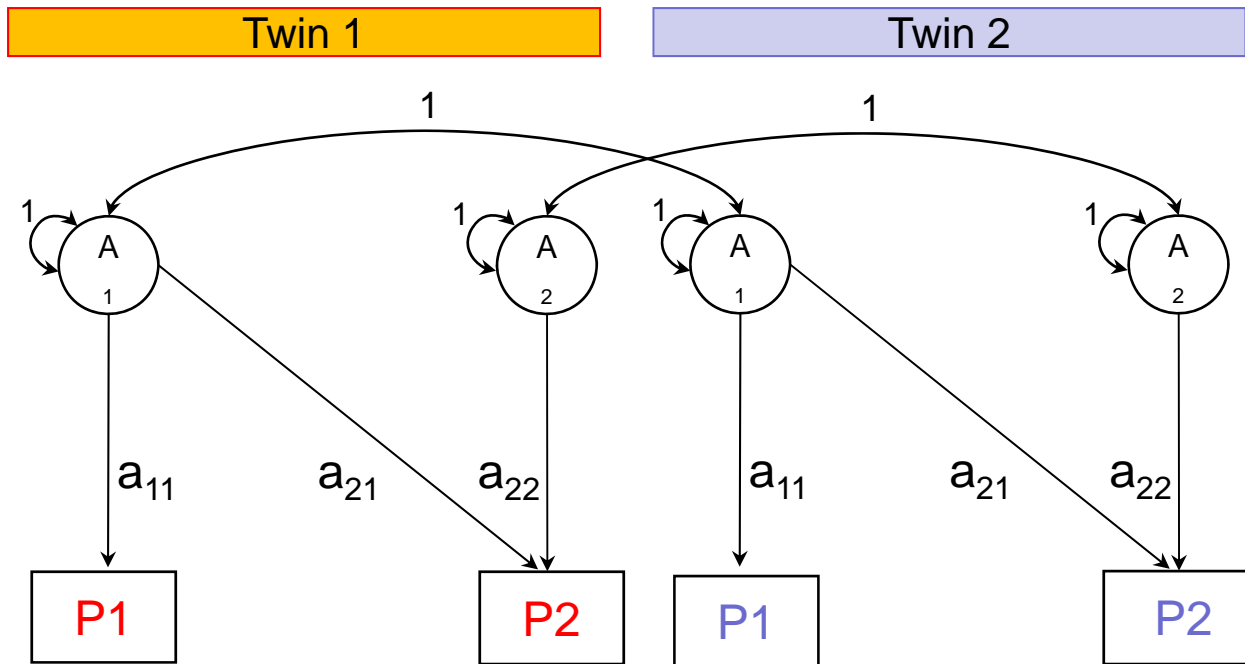
```
# Matrices generated to hold A, C, and E computed Variance Components
```

```
covA <- mxAlgebra(name = "A", expression = a %*% t(a))  
covC <- mxAlgebra(name = "C", expression = c %*% t(c))  
covE <- mxAlgebra(name = "E", expression = e %*% t(e))
```

```
# Algebra to compute total variances and standard deviations (diagonal only)
```

```
covPh <- mxAlgebra(name = "V", expression = A+C+E)  
matI <- mxMatrix(name = "I", type = "Iden", nrow = nv, ncol = nv)  
invSD <- mxAlgebra(name = "iSD", expression = solve(sqrt(I*V)))
```


MZ Cross-Twin Covariance (A)



Cross-twin within-trait:

$$P1-P1 = 1 * a_{11}^2$$

$$P2-P2 = 1 * a_{22}^2 + 1 * a_{21}^2$$

Cross-twin cross-trait:

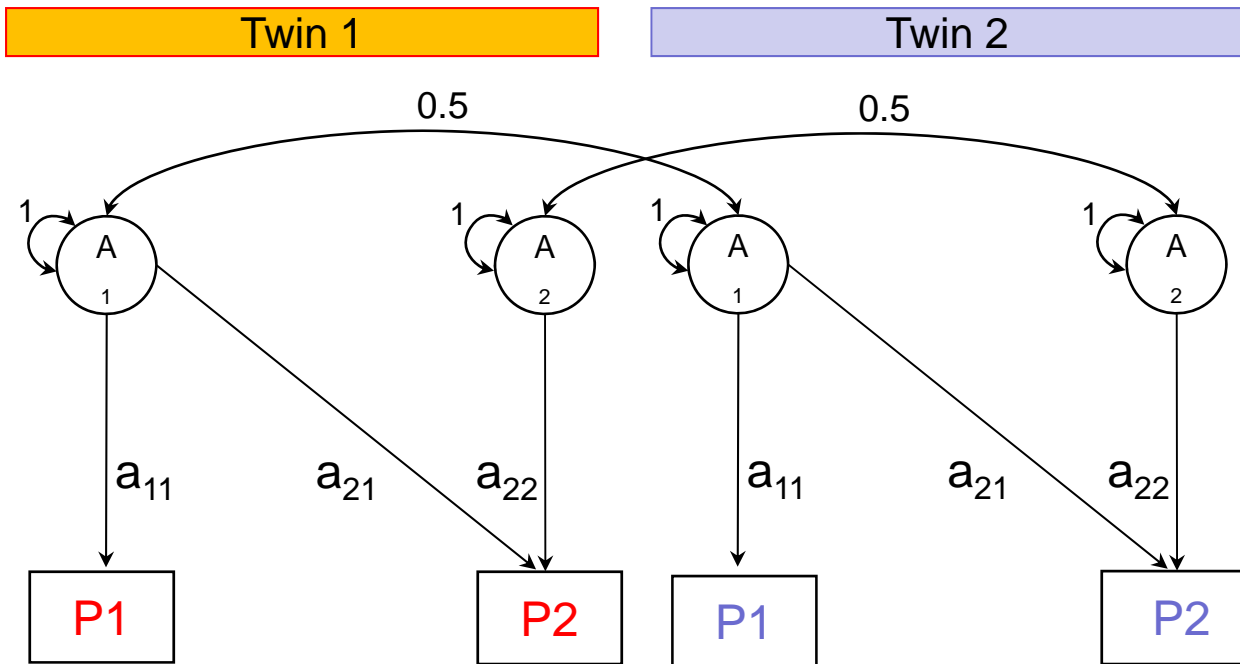
$$P1-P2 = 1 * a_{11} a_{21}$$

$$P2-P1 = 1 * a_{21} a_{11}$$

$$A = a \% * \% t(a)$$

$$= \begin{bmatrix} a_{11}^2 & a_{11} a_{21} \\ a_{21} a_{11} & (a_{21}^2 + a_{22}^2) \end{bmatrix}$$

DZ Cross-Twin Covariance (A)



Cross-twin within-trait:

$$P1-P1 = 0.5a_{11}^2$$

$$P2-P2 = 0.5a_{22}^2 + 0.5a_{21}^2$$

Cross-twin cross-trait:

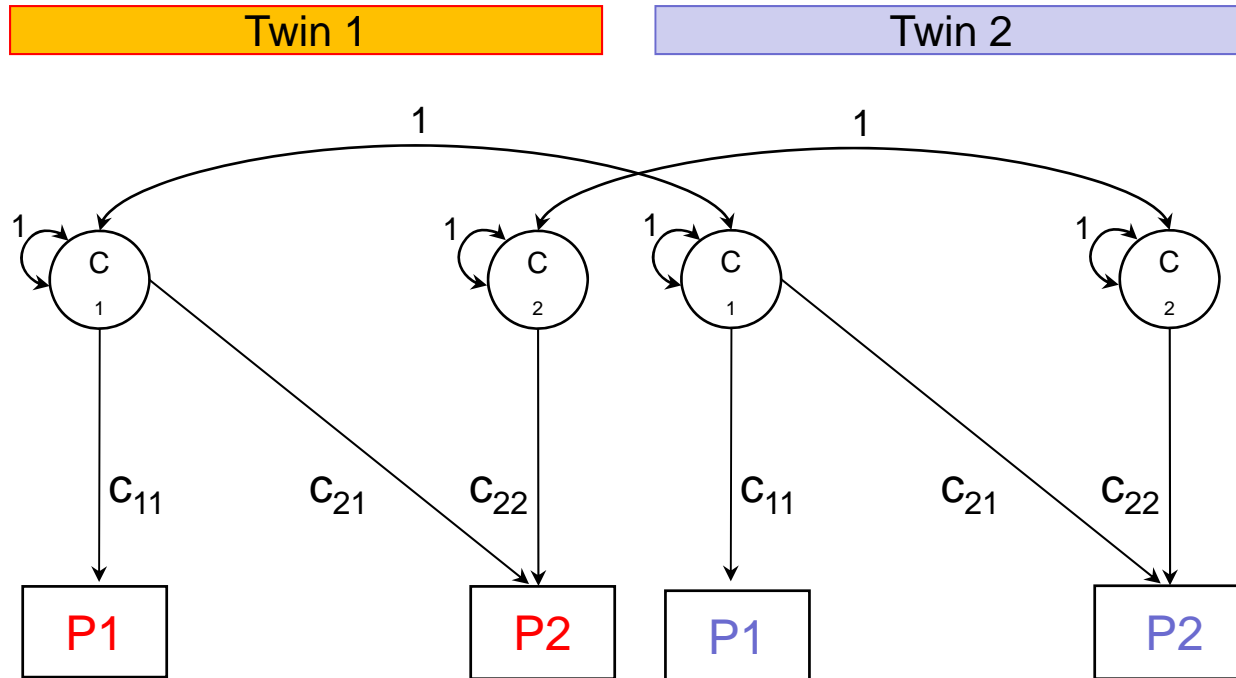
$$P1-P2 = 0.5a_{11}a_{21}$$

$$P2-P1 = 0.5a_{21}a_{11}$$

$$0.5 \times x \times A = 0.5 \times x \times (a \times t(a))$$

$$= \begin{bmatrix} 0.5a_{11}^2 & 0.5a_{11}a_{21} \\ 0.5a_{21}a_{11} & 0.5(a_{21}^2 + a_{22}^2) \end{bmatrix}$$

MZ/DZ Cross-Twin Covariance (C)



Cross-twin within-trait:

$$P1-P1 = 1 * C_{11}^2$$

$$P2-P2 = 1 * C_{22}^2 + 1 * C_{21}^2$$

Cross-twin cross-trait:

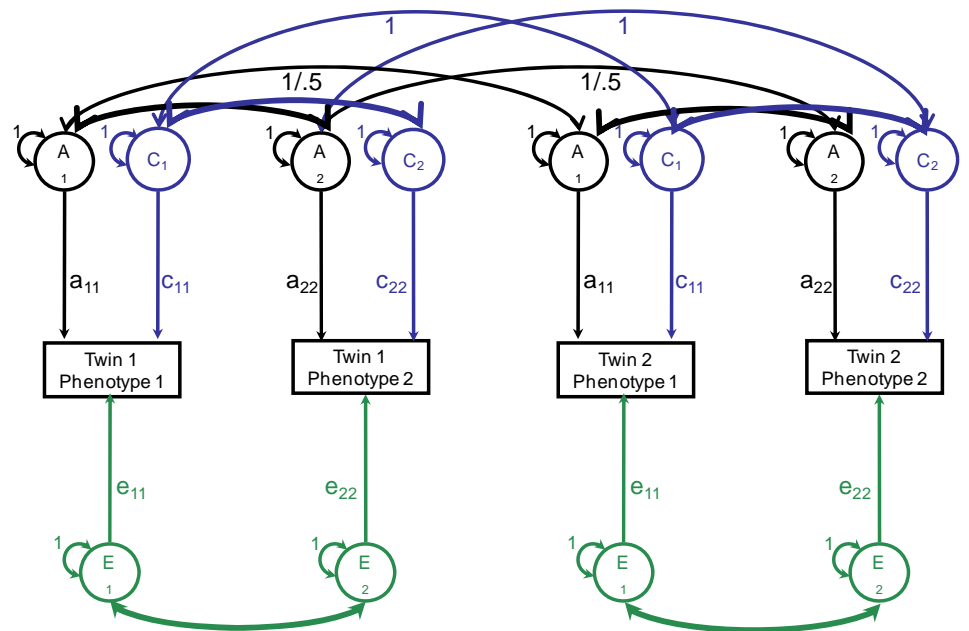
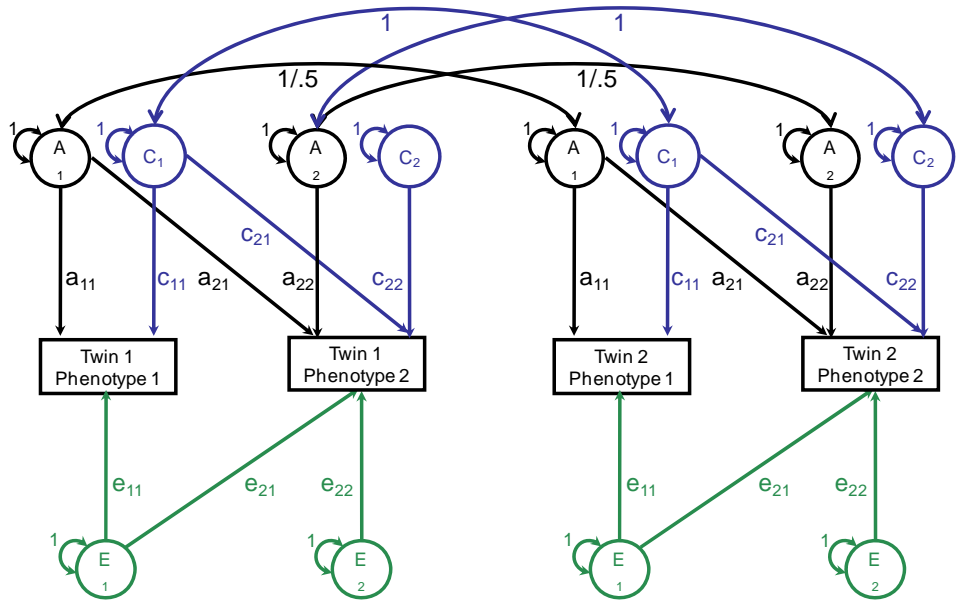
$$P1-P2 = 1 * C_{11} C_{21}$$

$$P2-P1 = 1 * C_{21} C_{11}$$

$$C = c \% * \% t(c)$$

$$= \begin{bmatrix} c_{11}^2 & c_{11} c_{21} \\ c_{21} c_{11} & (c_{21}^2 + c_{22}^2) \end{bmatrix}$$

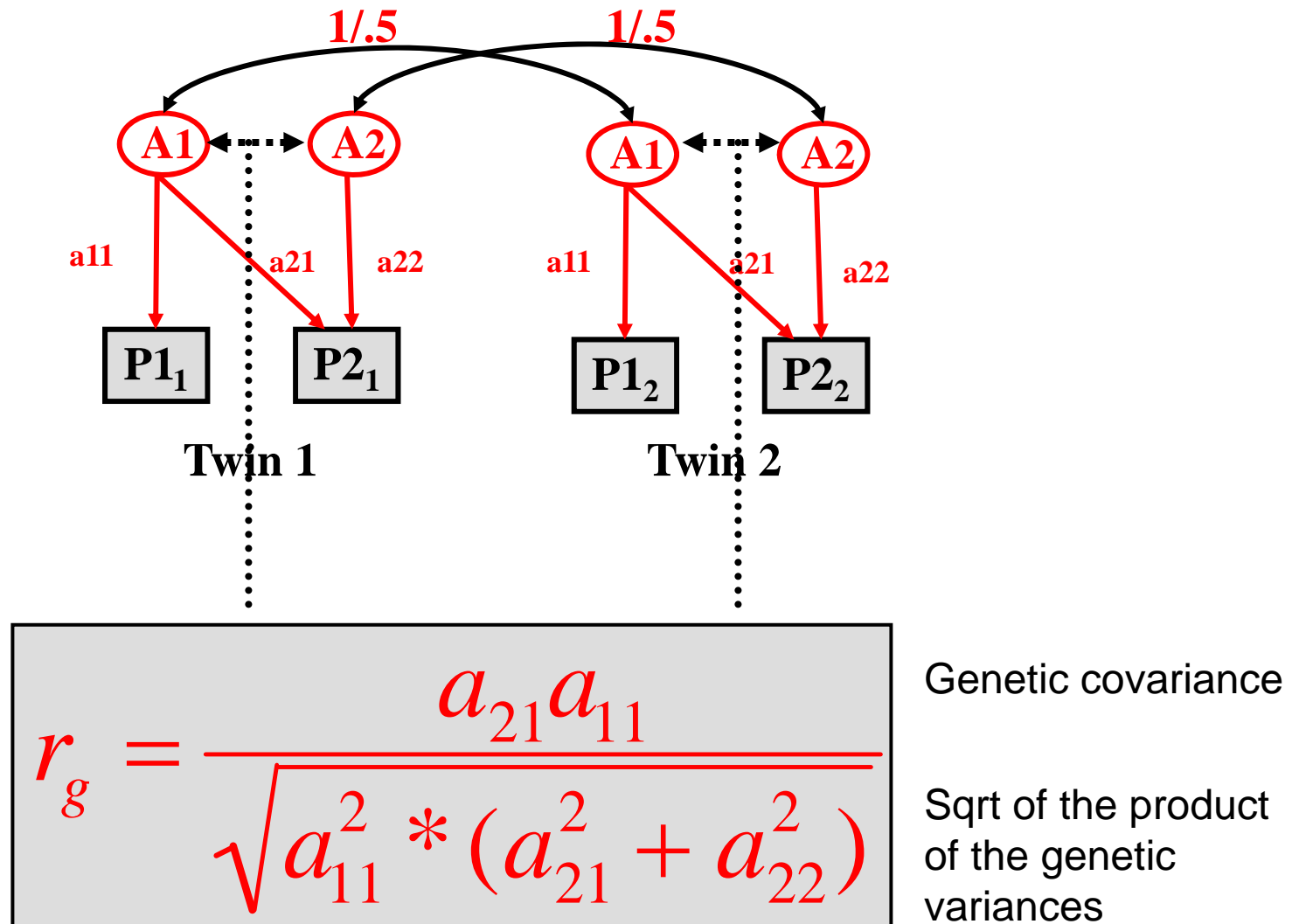
Unstandardized vs standardized solution



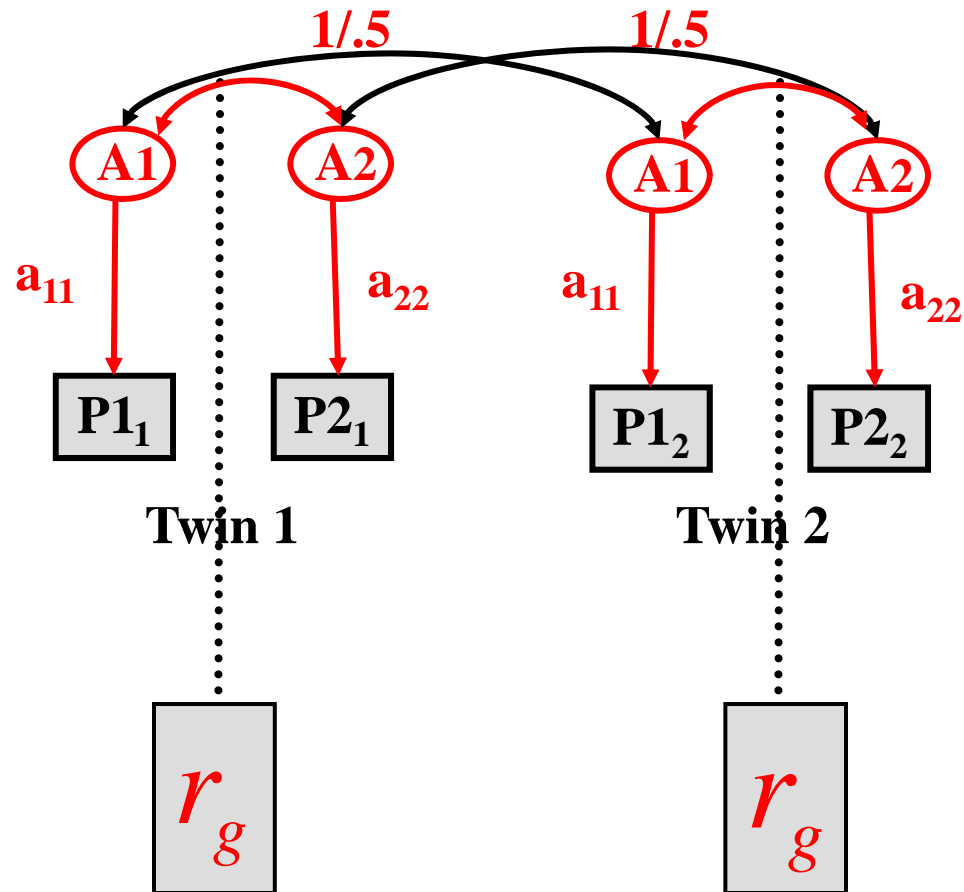
Genetic correlation

- It is calculated by dividing the genetic covariance by the square root of the product of the genetic variances of the two variables

Genetic correlation



Standardized Solution = Correlated Factors Solution



Genetic correlation – matrix algebra

$$\Sigma_A = \begin{bmatrix} a_{11}^2 & a_{11}a_{21} \\ a_{21}a_{11} & a_{21}^2 + a_{22}^2 \end{bmatrix}$$
$$= \begin{bmatrix} \sigma_{A_{11}}^2 & \sigma_{A_{12}}^2 \\ \sigma_{A_{21}}^2 & \sigma_{A_{22}}^2 \end{bmatrix}$$

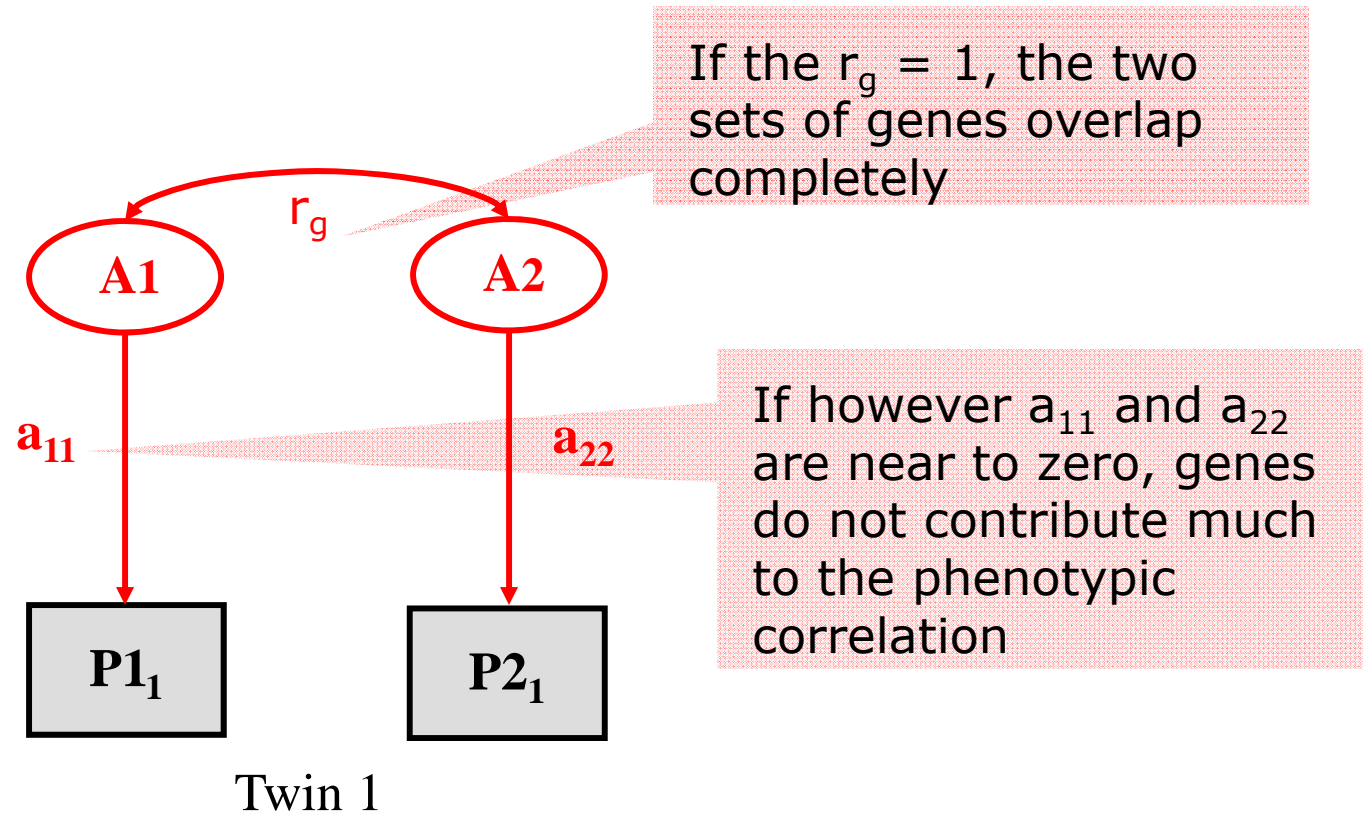
$$\begin{bmatrix} 1 & r_G \\ r_G & 1 \end{bmatrix} = \begin{bmatrix} \frac{1}{\sqrt{\sigma_{A_{11}}^2}} & 0 \\ 0 & \frac{1}{\sqrt{\sigma_{A_{22}}^2}} \end{bmatrix} * \begin{bmatrix} \sigma_{A_{11}}^2 & \sigma_{A_{12}}^2 \\ \sigma_{A_{21}}^2 & \sigma_{A_{22}}^2 \end{bmatrix} * \begin{bmatrix} \frac{1}{\sqrt{\sigma_{A_{11}}^2}} & 0 \\ 0 & \frac{1}{\sqrt{\sigma_{A_{22}}^2}} \end{bmatrix}$$

OpenMx

OpenMx

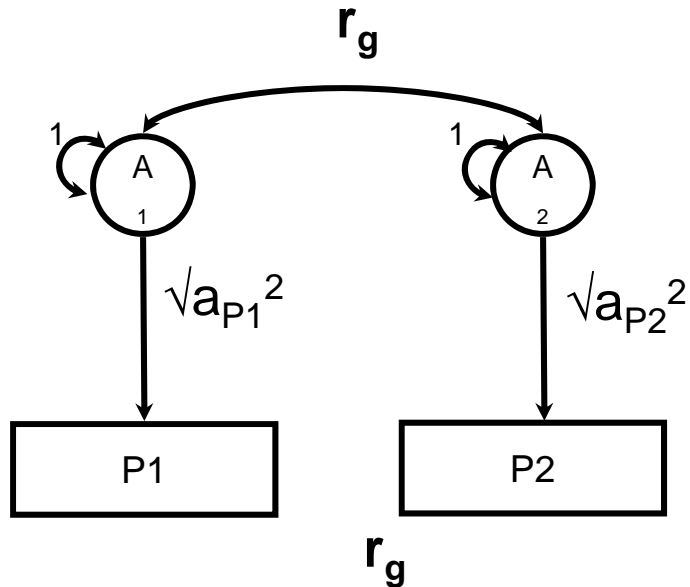
```
corA <- mxAlgebra(name = "rA", expression = solve(sqrt(I*A))%*%A%*%solve(sqrt(I*A)))
```

Contribution to phenotypic correlation



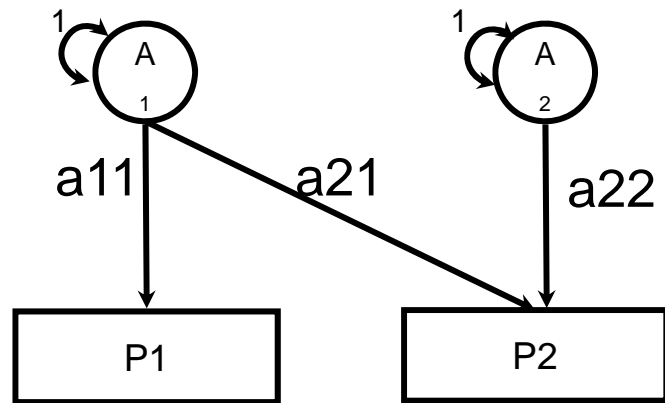
- The contribution to the phenotypic correlation is a function of both heritabilities and the r_g

Contribution to phenotypic correlation



Proportion of $r_{P1,P2}$ due to additive genetic factors:

$$\frac{\left(\sqrt{a_{P1}^2} * r_g * \sqrt{a_{P2}^2} \right)}{r_{P1,P2}}$$



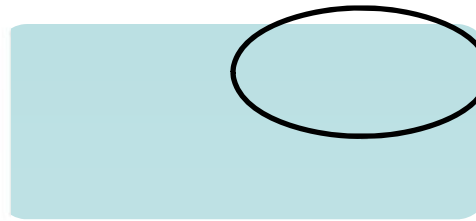
$$\frac{a_{21}a_{11}}{a_{21}a_{11} + c_{21}c_{11} + e_{21}e_{11}}$$

Contribution to phenotypic correlation

OpenMx

```
ACEcovMatrices <- c("A","C","E","V","AV","CV","EV")
ACEcovLabels <-
("covComp_A","covComp_C","covComp_E","Var","stCovComp_A","stCovComp_C","stCovComp_E")
formatOutputMatrices(CholACEFit,ACEcovMatrices,ACEcovLabels,Vars,4)
```

```
[1] "Matrix ACE.A/ACE.V"
      stCovComp_A1 stCovComp_A2
LP1 0.2491        0.4784
LP2 0.4784        0.2673
```



Proportion of the phenotypic correlation due to genetic effects

```
[1] "Matrix ACE.C/ACE.V"
      stCovComp_C1 stCovComp_C2
LP1 0.2441        0.2417
LP2 0.2417        0.0292
```



Proportion of the phenotypic correlation due to shared environmental effects

```
[1] "Matrix ACE.E/ACE.V"
      stCovComp_E1 stCovComp_E2
LP1 0.5069        0.2799
LP2 0.2799        0.7035
```



Proportion of the phenotypic correlation due to unshared environmental effects

Summary / Interpretation

- Genetic correlation (r_g) = the correlation between two latent genetic factors
 - High genetic correlation = large overlap in genetic effects on the two phenotypes
- Contribution of genes to phenotypic correlation = The proportion of the phenotypic correlation explained by the overlapping genetic factors
 - This is a function of the r_g and the heritabilities of the two traits

Outline

- 11.00-12.30
 - Lecture Bivariate Cholesky Decomposition
 - Practical Bivariate analysis of IQ and attention problems
- 12.30-13.30 LUNCH
- 13.30-15.00
 - Lecture Multivariate Cholesky Decomposition
 - Practical Tri- and Four-variate analysis of IQ, educational attainment and attention problems

Practical

- Replicate findings from Kuntsi et al.
- 126 MZ and 126 DZ twin pairs from Netherlands Twin Register
- Age 12
- FSIQ
- Attention Problems (AP) [mother-report]

Practical – exercise 1

- Script CholeskyBivariate.R
- Dataset Cholesky.dat
- Run script **up to saturated model**

Practical – exercise 1

- Fill in the table with correlations:

MZ	FSIQ1	AP1	FSIQ2	AP2
FSIQ1	1			
AP1		1		
FSIQ2			1	
AP2				1

DZ	FSIQ1	AP1	FSIQ2	AP2
FSIQ1	1			
AP1		1		
FSIQ2			1	
AP2				1

Practical – exercise 1 - Questions

- Are correlations similar to those reported by Kuntsi et al.?
- What is the phenotypic correlation between FSIQ and AP?
- What are the MZ and DZ cross-twin cross-trait correlations?
- What are your expectations for the common aetiological influences?
 - Are they familial?
 - If yes, are they genetic or shared environmental?

Practical – exercise 2

- Run **Bivariate ACE model** in the script
- Look whether you understand the output. If not, ask us!
- Adapt the first submodel such that you drop all C
- Compare fit of AE model with ACE model

Script: CholeskyBivariate.R

Practical – exercise 2

- Fill in the table with fit statistics:

	-2LL	df	chi2	Δ df	P-value
ACE model			-	-	-
AE model					

- Question:
 - Is C significant?

Practical – exercise 3

- Now try to fill in the estimates for all paths in the path model (grey boxes):

