

Univariate ACE Model

Boulder Workshop 2014
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Questions to be Answered

- Does a trait of interest cluster among related individuals?
- Can clustering be explained by genetic or environmental effects?
- What is the best way to explain the degree to which genetic and environmental effects affect a trait?

Practical Example

- Dataset: NH&MRC Twin Register
- 1981 Questionnaire
- BMI (body mass index): weight/height squared
- Young Female Cohort: 18-30 years
- Sample Size:
 - MZf_young: 534 pairs ($\text{zyg}=1$)
 - DZf_young: 328 pairs ($\text{zyg}=3$)

Dataset

```
> head(twinData)
```

Univariate Twin Saturated

twinSatConCov.R [1]

```
#-----  
# Program: twinSatConCov.R  
# Author: Hermine Maes  
# Date: 03 03 2014  
#  
# Univariate Twin Saturated model to estimate means and (co)variances  
# Matrix style model - Raw data - Continuous data  
#-----|-----|-----|-----|-----|-----|-----|-----  
  
# Load Libraries  
require(OpenMx)  
require(psych)  
  
# PREPARE DATA  
# Load Data  
data(twinData)  
dim(twinData)  
describe(twinData, skew=F)
```

Univariate Twin Saturated

twinSatConCov.R [2]

```
# Select Variables for Analysis
Vars      <- 'bmi'
nv        <- 1                      # number of variables
ntv       <- nv*2                   # number of total variables
selVars   <- paste(Vars,c(rep(1,nv),rep(2,nv)),sep="")  #c('bmi1','bmi2')

# Select Covariates for Analysis
twinData[, 'age'] <- twinData[, 'age']/100
twinData  <- twinData[-which(is.na(twinData$age)),]
covVars   <- 'age'

# Select Data for Analysis
mzData    <- subset(twinData, zyg==1, c(selVars, covVars))
dzData    <- subset(twinData, zyg==3, c(selVars, covVars))

# Set Starting Values
svMe      <- 20      # start value for means
svVa      <- .8       # start value for variance
lbVa      <- .0001    # start value for lower bounds
svVas    <- diag(svVa,ntv,ntv)
lbVas    <- diag(lbVa,ntv,ntv)
laMeMZ   <- c("m1MZ","m2MZ")        # labels for means for MZ twins
laMeDZ   <- c("m1DZ","m2DZ")        # labels for means for DZ twins
laVaMZ   <- c("v1MZ","c21MZ","v2MZ") # labels for (co)variances for MZ twins
laVaDZ   <- c("v1DZ","c21DZ","v2DZ") # labels for (co)variances for DZ twins
```

My Naming Conventions

name of variable(s)	Vars	<- 'bmi'
number of variables	nv	<- 1
number of twin variables	ntv	<- nv*2
variables per twin pair	selVars	<-c('bmi1','bmi2')
number of factors	nf	<- 2
number of thresholds	nth	<- 3
MZ data	mzData	
DZ data	dzData	
starting values	sv	
lower bound / upper bound	lb / ub	
labels	la	

Classical Twin Study

Background

- The Classical Twin Study (CTS) uses MZ and DZ twins reared together
 - MZ twins share 100% of their genes
 - DZ twins share on average 50% of their genes
- Expectation: Genetic factors are assumed to contribute to a phenotype when MZ twins are more similar than DZ twins

Classical Twin Study Assumptions

- Equal Environments of MZ and DZ pairs
- Random Mating
- No GE Correlation
- No G x E Interaction
- No Sex Limitation
- No G x age Interaction

Classical Twin Study

Basic Data Assumptions

- MZ and DZ twins are sampled from the same population, therefore we expect :
 - Equal means/variances in Twin 1 and Twin 2
 - Equal means/variances in MZ and DZ twins
- Further assumptions would need to be tested if we introduce male twins and opposite sex twin pairs

‘Old Fashioned’ Data Checking

	MZ		DZ	
	T1	T2	T1	T2
mean	21.35	21.34	21.45	21.46
variance	0.73	0.79	0.77	0.82
covariance		0.59		0.25

Nice, but how can we actually be sure that these means and variances are truly the same?

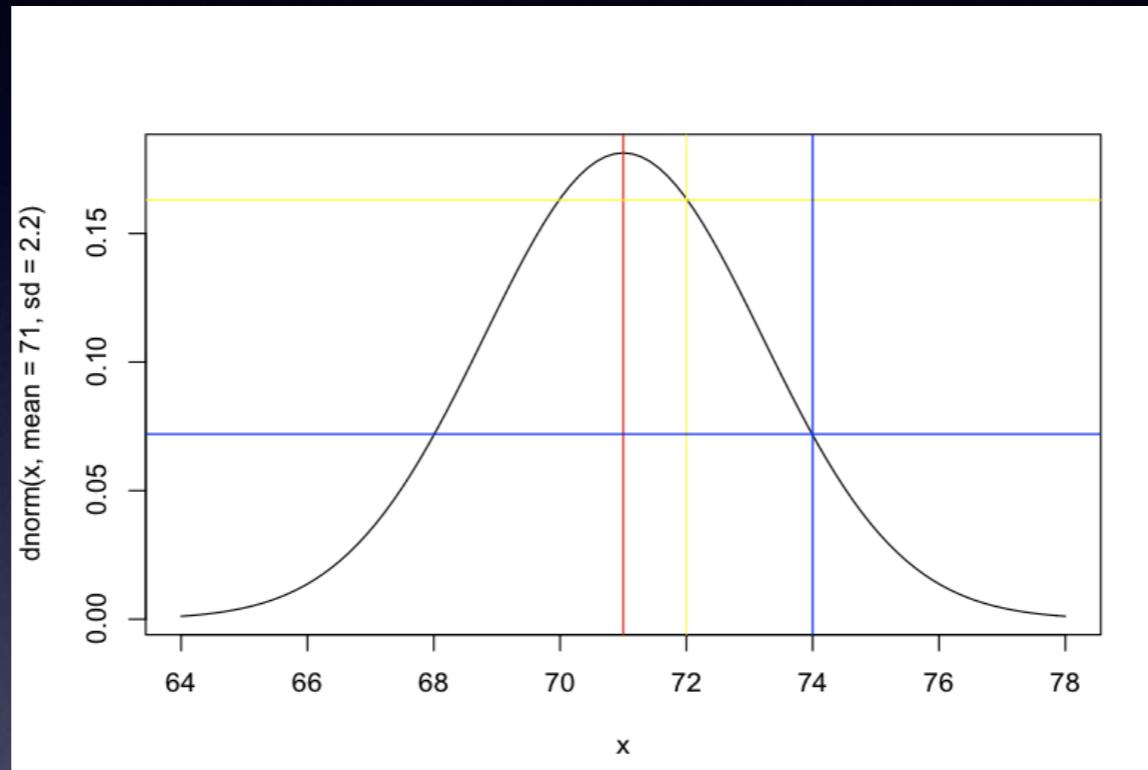
Univariate Analysis

A Roadmap

- I. Use data to test basic assumptions (equal means & variances for twin 1/twin 2 and MZ/DZ pairs)
 - Saturated Model
2. Estimate contributions of genetic/environmental effects on total variance of a phenotype
 - ACE or ADE Models
3. Test ACE (ADE) submodels to identify and report significant genetic and environmental contributions
 - AE or CE or E Only Models

Probability Density Function

$\Phi(x_i)$



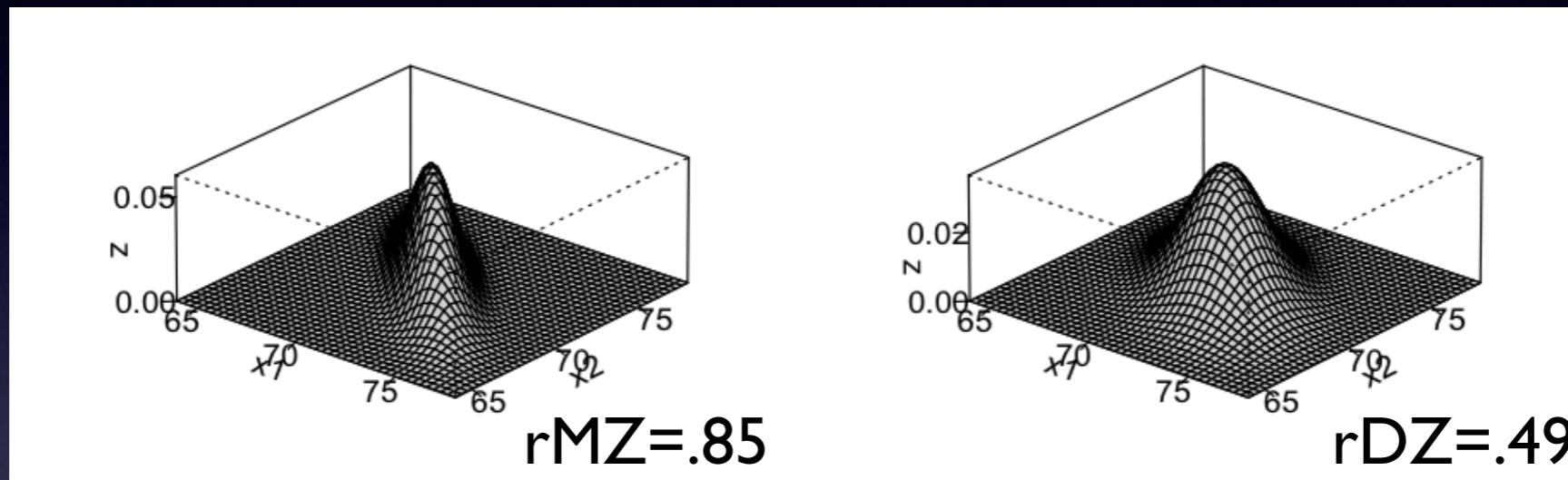
$\Phi(x_i)$ is likelihood of data point x_i for particular mean and variance estimates

$$\Phi(x_i) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x_i - \mu)^2}{2\sigma^2}}$$

π : pi=3.14; x_i : observed value of variable i; μ : expected mean; σ : expected variance

Univariate: height of probability density function

Multinormal Probability Function



$\Phi(x_i)$ is likelihood of pair of data points x_i and y_i
for particular means, variances and correlation estimates

$$\Phi(x_i) = - |2\pi\Sigma|^{-n/2} e^{-0.5((x_i - \mu)\Sigma^{-1}(x_i - \mu)')}$$

$\pi=3.14$; x_i : value of variable i; μ : expected mean; Σ : expected covariance matrix

Multivariate: height of multinormal probability density function

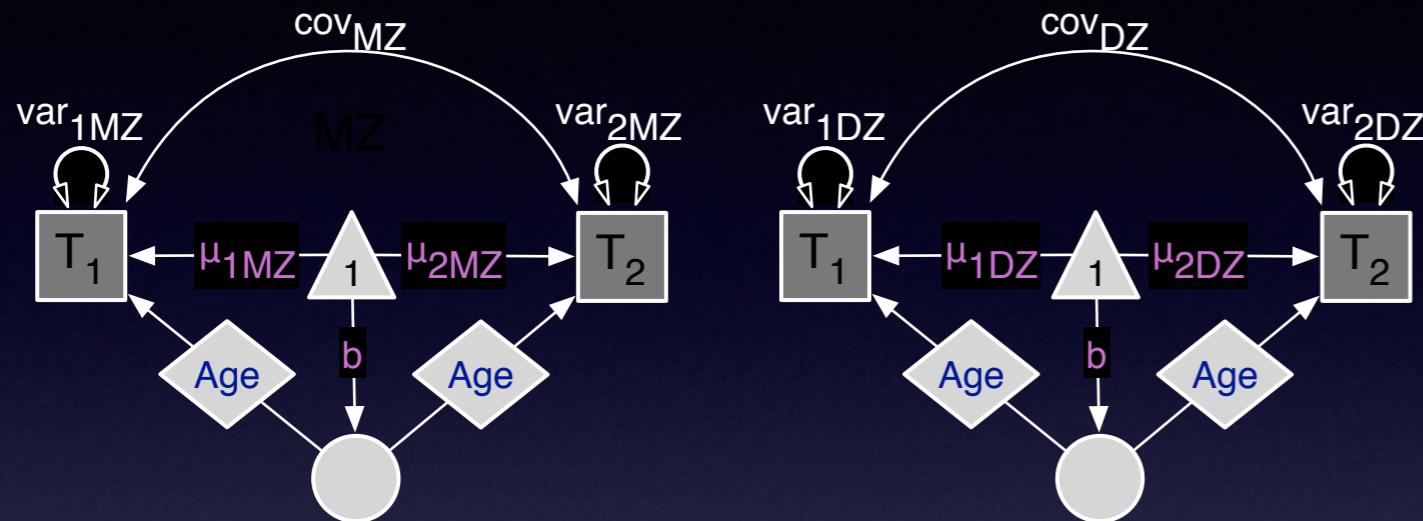
Intuition behind Maximum Likelihood (ML)

- Likelihood: probability that an observation (data point) is predicted by specified model
- For MLE, determine most likely values of population parameter value (e.g, μ , σ , β) given observed sample value
 - define model
 - define probability of observing a given event conditional on a particular set of parameters
 - choose a set of parameters which are most likely to have produced observed results

Likelihood Ratio Test

- Likelihood Ratio test is a simple comparison of Log Likelihoods under 2 separate models:
 - Model Mu is Unconstrained (has more parameters)
 - Model Mc is Constrained (has fewer parameters)
- LR statistic equals:
 - $\text{LR} (\text{Mc} | \text{Mu}) = 2\ln(L(\text{Mu}) - 2\ln(L(\text{Mc}))$
- LR is asymptotically distributed as χ^2 with the df equal to the number of constraints

Predicted Means



1×2 matrices

T1	T2
$m1MZ + b * Age$	$m2MZ + b * Age$

T1	T2
$m1DZ + b * Age$	$m2DZ + b * Age$

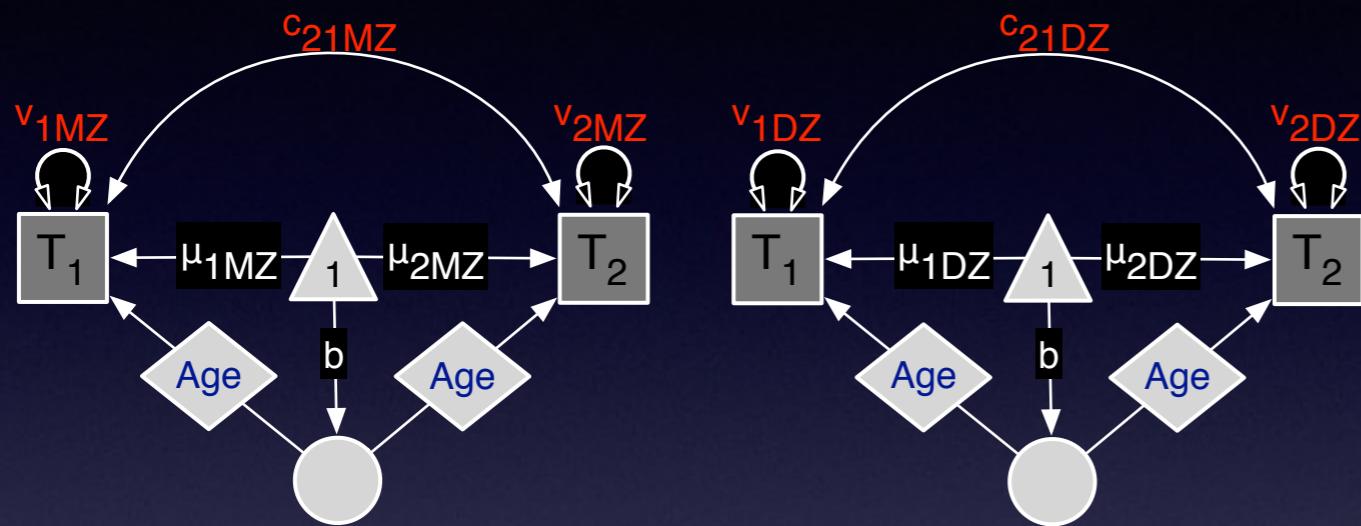
```

defAge      <- mxMatrix( type="Full", nrow=1, ncol=1,
  free=FALSE, labels=c("data.age"), name="Age" )
pathB       <- mxMatrix( type="Full", nrow=1, ncol=1,
  free=TRUE, values= .01, label="l11", name="b" )
laMeMZ     <- c("m1MZ","m2MZ"); laMeDZ    <- c("m1DZ","m2DZ")

meanMZ      <- mxMatrix( type="Full", nrow=1, ncol=ntv,
  free=TRUE, values=svMe, labels=laMeMZ, name="MeanMZ")
meanDZ      <- mxMatrix( type="Full", nrow=1, ncol=ntv,
  free=TRUE, values=svMe, labels=laMeDZ, name="MeanDZ")
expMeanMZ <- mxAlgebra( expression= meanMZ +
  cbind(b%*%Age,b%*%Age), name="expMeanMZ" )
expMeanDZ <- mxAlgebra( expression= meanDZ +
  cbind(b%*%Age,b%*%Age), name="expMeanDZ" )

```

Predicted Covariances



2x2 matrices

	T1	T2
T1	v_{1MZ}	c_{21MZ}
T2	c_{21MZ}	v_{2MZ}

	T1	T2
T1	v_{1DZ}	c_{21DZ}
T2	c_{21DZ}	v_{2DZ}

```

laVaMZ    <- c("v1MZ", "c21MZ", "v2MZ")
laVaDZ    <- c("v1DZ", "c21DZ", "v2DZ")

covMZ     <- mxMatrix( type="Symm", nrow=ntv, ncol=ntv,
free=TRUE, values=svVas, lbound=lbVas, labels=laVaMZ,
name="expCovMZ" )
covDZ     <- mxMatrix( type="Symm", nrow=ntv, ncol=ntv,
free=TRUE, values=svVas, lbound=lbVas, labels=laVaDZ,
name="expCovDZ" )

```

Univariate Twin Saturated

twinSatCon.R [3]

```
# Matrices for Covariates and linear Regression Coefficients
defAge    <- mxMatrix( type="Full", nrow=1, ncol=1, free=FALSE,
                     labels=c("data.age"), name="Age")
pathB     <- mxMatrix( type="Full", nrow=1, ncol=1, free=TRUE,
                     values=.01, label="l11", name="b")

# Algebra for expected Mean Matrices in MZ & DZ twins
meanMZ   <- mxMatrix( type="Full", nrow=1, ncol=ntv, free=TRUE, values=svMe,
                     labels=laMeMZ, name="meanMZ" )
meanDZ   <- mxMatrix( type="Full", nrow=1, ncol=ntv, free=TRUE, values=svMe,
                     labels=laMeDZ, name="meanDZ" )
expMeanMZ <- mxAlgebra( expression= meanMZ + cbind(b%*%Age,b%*%Age), name="expMeanMZ" )
expMeanDZ <- mxAlgebra( expression= meanDZ + cbind(b%*%Age,b%*%Age), name="expMeanDZ" )

# Algebra for expected Variance/Covariance Matrices in MZ & DZ twins
expCovMZ <- mxMatrix( type="Symm", nrow=ntv, ncol=ntv, free=TRUE,
                      values=svVas, lbound=lbVas, labels=laVaMZ, name="expCovMZ" )
expCovDZ <- mxMatrix( type="Symm", nrow=ntv, ncol=ntv, free=TRUE,
                      values=svVas, lbound=lbVas, labels=laVaDZ, name="expCovDZ" )
```

Univariate Twin Saturated

twinSatCon.R [4]

```
# Data objects for Multiple Groups
dataMZ    <- mxData( observed=mzData, type="raw" )
dataDZ    <- mxData( observed=dzData, type="raw" )

# Objective objects for Multiple Groups
objMZ    <- mxFIMLObjective( covariance="expCovMZ", means="expMeanMZ",
                           dimnames=selVars )
objDZ    <- mxFIMLObjective( covariance="expCovDZ", means="expMeanDZ",
                           dimnames=selVars )

# Combine Groups
modelMZ   <- mxModel( "MZ", defAge, pathB, meanMZ, expMeanMZ, expCovMZ, dataMZ,
                      objMZ )
modelDZ   <- mxModel( "DZ", defAge, pathB, meanDZ, expMeanDZ, expCovDZ, dataDZ,
                      objDZ )
minus2ll  <- mxAlgebra( MZ.objective+ DZ.objective, name="minus2sumloglikelihood" )
obj      <- mxFitFunctionAlgebra( "minus2sumloglikelihood" )
ciCov    <- mxCI( c('MZ.expCovMZ','DZ.expCovDZ' ) )
ciMean   <- mxCI( c('MZ.expMeanMZ','DZ.expMeanDZ' ) )
twinSatModel <- mxModel( "twinSat", modelMZ, modelDZ, minus2ll, obj,
                         ciCov, ciMean )
```

Univariate Twin Saturated

twinSatCon.R [5]

```
#-----
# RUN MODEL

# Run Saturated Model
twinSatFit      <- mxRun( twinSatModel, intervals=F )
twinSatSum     <- summary( twinSatFit )
twinSatSum

# Generate Saturated Model Output
twinSatFit$MZ.expMeanMZ@result
twinSatFit$DZ.expMeanDZ@result
twinSatFit$MZ.expCovMZ@values
twinSatFit$DZ.expCovDZ@values

twinSatSum$observedStatistics
length(twinSatSum$parameters[[1]])
twinSatFit@output$Minus2LogLikelihood
twinSatSum$degreesOfFreedom
twinSatSum$AIC
round(twinSatFit@output$estimate,4)
```

summary(MxModel)

free parameters:

	name	matrix	row	col	Estimate	Std.Error	lbound
1	l11	MZ.b	1	1	2.7536831	0.69736577	
2	mMZ1	MZ.meanMZ	1	1	20.6886948	0.16989840	
3	mMZ2	MZ.meanMZ	1	2	20.6934721	0.17017616	
4	vMZ1	MZ.expCovMZ	bmi1	bmi1	0.7213571	0.04326293	1e-04
5	cMZ21	MZ.expCovMZ	bmi1	bmi2	0.5840681	0.04034558	0
6	vMZ2	MZ.expCovMZ	bmi2	bmi2	0.7842634	0.04713262	1e-04
7	mDZ1	DZ.meanDZ	1	1	20.7833537	0.17217692	
8	mDZ2	DZ.meanDZ	1	2	20.8080578	0.17278599	
9	vDZ1	DZ.expCovDZ	bmi1	bmi1	0.7281361	0.05594823	1e-04
10	cDZ21	DZ.expCovDZ	bmi1	bmi2	0.2414624	0.04378434	0
11	vDZ2	DZ.expCovDZ	bmi2	bmi2	0.8030416	0.06183128	1e-04

observed statistics: 1775

estimated parameters: 11

degrees of freedom: 1764

-2 log likelihood: 4015.118

number of observations: 919

Information Criteria AIC: 1837.118

Estimated Values

		T1	T2		T1	T2
Saturated Model						
mean	MZ	20.68	20.69	DZ	20.78	20.80
cov	T1	0.72		T1	0.73	
	T2	0.58	0.78	T2	0.24	0.80

11 parameters Estimated: |||
m1MZ, m2MZ, v1MZ, v2MZ, c21MZ
m1DZ, m2DZ, v1DZ, v2DZ, c21DZ

Goodness-of-Fit Statistics

	ep	-2ll	df	AIC	diff -2ll	diff df	P
Sat	11	4015.12	1764	487.12			

os	observed statistics	
ep	estimated parameters	
-2ll	-2 LogLikelihood	
df	degrees of freedom	os - ep
AIC	Akaike's Information Criterion	-2ll -2df
diff -2ll	likelihood ratio Chi-square	
diff df	difference in degrees of freedom	

Fitting Submodels

```
# Test significance of Covariate  
  
# Copy model, provide new name  
testCovModel    <- mxModel(twinSatFit, name="testCov")  
  
# Change parameter by changing attributes for label  
testCovModel    <- omxSetParameters( testCovModel,  
label="l11", free=FALSE, values=0 )  
  
# Fit Nested Model  
testCovFit      <- mxRun(testCovModel)  
  
# Compare Nested Model with 'Full' Model  
mxCompare(twinSatFit, testCovFit)
```

Goodness-of-Fit Stats

	ep	-2ll	df	AIC	diff -2ll	diff df	P
Saturated	11	4015.12	1764	487.12			
drop beta	10	4030.57	1765	500.57	15.45	1	0

Fitting Nested Models

- **Saturated Model**
 - likelihood of data without any constraints
 - fitting as many means and (co)variances as possible
- **Equality of means & variances by twin order**
 - test if mean of twin 1 = mean of twin 2
 - test if variance of twin 1 = variance of twin 2
- **Equality of means & variances by zygosity**
 - test if mean of MZ = mean of DZ
 - test if variance of MZ = variance of DZ

Equate Means across twin order

twinSatCon.R [7]

```
# -----  
# RUN SUBMODELS  
  
# Constrain expected Means to be equal across twin order  
eqMeansTwinModel      <- mxModel(twinSatFit, name="eqMeansTwin" )  
eqMeansTwinModel      <- omxSetParameters( eqMeansTwinModel,  
  label=c("m1MZ","m2MZ"), free=TRUE, values=svMe, newlabels='mMZ' )  
eqMeansTwinModel      <- omxSetParameters( eqMeansTwinModel,  
  label=c("m1DZ","m2DZ"), free=TRUE, values=svMe, newlabels='mDZ' )  
  
eqMeansTwinFit        <- mxRun( eqMeansTwinModel, intervals=F )  
eqMeansTwinSum         <- summary( eqMeansTwinFit )  
eqMeansTwinLLL         <- eqMeansTwinFit@output$Minus2LogLikelihood  
  
twinSatLLL            <- twinSatFit@output$Minus2LogLikelihood  
chi2Sat_eqM            <- eqMeansTwinLLL-twinSatLLL  
pSat_eqM               <- pchisq( chi2Sat_eqM, lower.tail=F, 2)  
chi2Sat_eqM; pSat_eqM  
mxCompare(twinSatFit, eqMeansTwinFit)
```

Equate Means & Variances across twin order & zygosity

twinSatCon.R [8]

```
# Constrain expected Means and Variances to be equal across twin order
eqMVarsTwinModel      <- mxModel(eqMeansTwinFit, name="eqMVarsTwin" )
eqMVarsTwinModel      <- omxSetParameters( eqMVarsTwinModel,
  label=c("v1MZ","v2MZ"), free=TRUE, values=svMe, newlabels='vMZ' )
eqMVarsTwinModel      <- omxSetParameters( eqMVarsTwinModel,
  label=c("v1DZ","v2DZ"), free=TRUE, values=svMe, newlabels='vDZ' )
eqMVarsTwinFit        <- mxRun( eqMVarsTwinModel, intervals=F )
subs <- list(eqMeansTwinFit, eqMVarsTwinFit)
mxCompare(twinSatFit, subs)

# Constrain expected Means and Variances to be equal across order and zygosity
eqMVarsZygModel       <- mxModel(eqMVarsTwinModel, name="eqMVarsZyg" )
eqMVarsZygModel       <- omxSetParameters( eqMVarsZygModel,
  label=c("mMZ","mDZ"), free=TRUE, values=svMe, newlabels='mZ' )
eqMVarsZygModel       <- omxSetParameters( eqMVarsZygModel,
  label=c("vMZ","vDZ"), free=TRUE, values=svMe, newlabels='vZ' )
eqMVarsZygFit         <- mxRun( eqMVarsZygModel, intervals=F )
mxCompare(eqMVarsTwinFit, eqMVarsZygFit)
```

Estimated Values

		T1	T2		T1	T2
Equate Means & Variances across Twin Order						
mean	MZ			DZ		
cov	T1			T1		
	T2			T2		
Equate Means Variances across Twin Order & Zygosity						
mean	MZ			DZ		
cov	T1			T1		
	T2			T2		

Goodness-of-Fit Stats

	ep	-2II	df	AIC	diff -2II	diff df	P
Saturated							
$mT1 = mT2$							
$mT1 = mT2$ $\text{var}T1 = \text{var}T2$							
Zyg $MZ = DZ$							

Goodness-of-Fit Stats

	ep	-2ll	df	AIC	diff -2ll	diff df	P
Saturated	11	4015.12	1764	487.12			
mT1=mT2	9	4015.35	1766	483.35	0.23	2	0.89
mT1=mT2 varT1=varT2	7	4018.61	1768	482.61	3.49	4	0.48
Zyg MZ=DZ	5	4022.79	1779	482.78	7.67	6	0.26

Patterns of Twin Correlations



$r_{MZ} = 2r_{DZ}$
Additive

*DZ twins
on average
share 50% of
additive
effects*

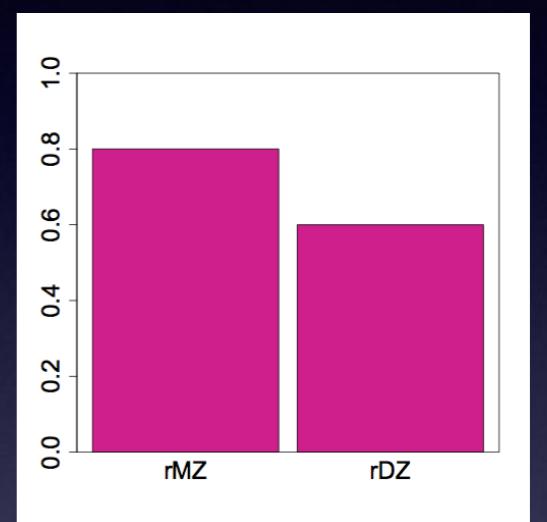


$r_{MZ} = r_{DZ}$
Shared
Environment



$r_{MZ} > 2r_{DZ}$
Additive &
Dominance

*DZ twins
on average share
25% of
dominance
effects*



$r_{DZ} > \frac{1}{2} r_{MZ}$
Additive &
Shared
Environment

$$\begin{aligned}A &= 2(r_{MZ}-r_{DZ}) \\C &= 2r_{DZ} - r_{MZ} \\E &= 1 - r_{MZ}\end{aligned}$$

Twin Correlations ~ Sources of Variance

I-rMZ

E

rMZ > rDZ

A

rMZ = 2 rDZ

only A

rMZ = rDZ

only C

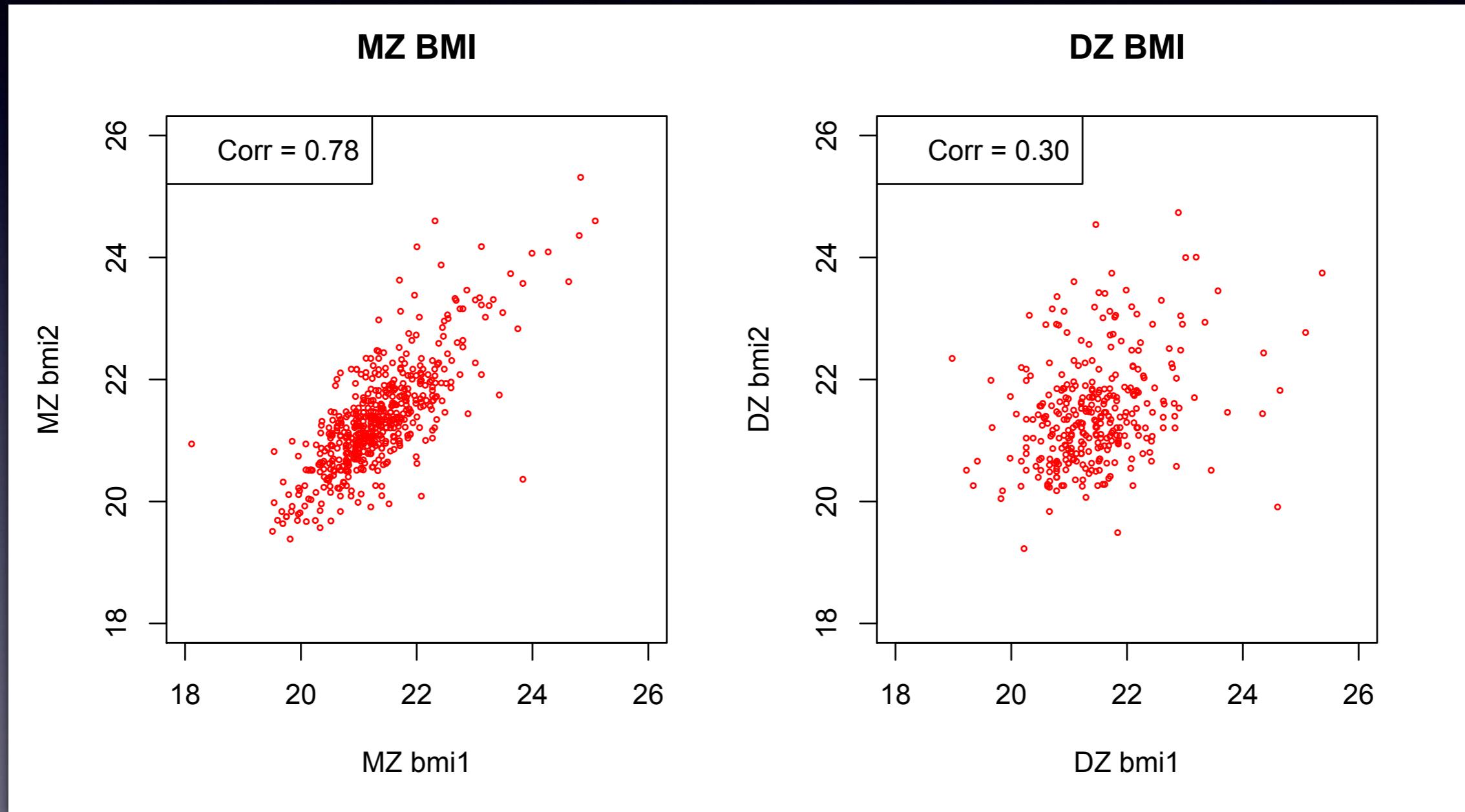
rMZ < 1/2 rDZ

A & C

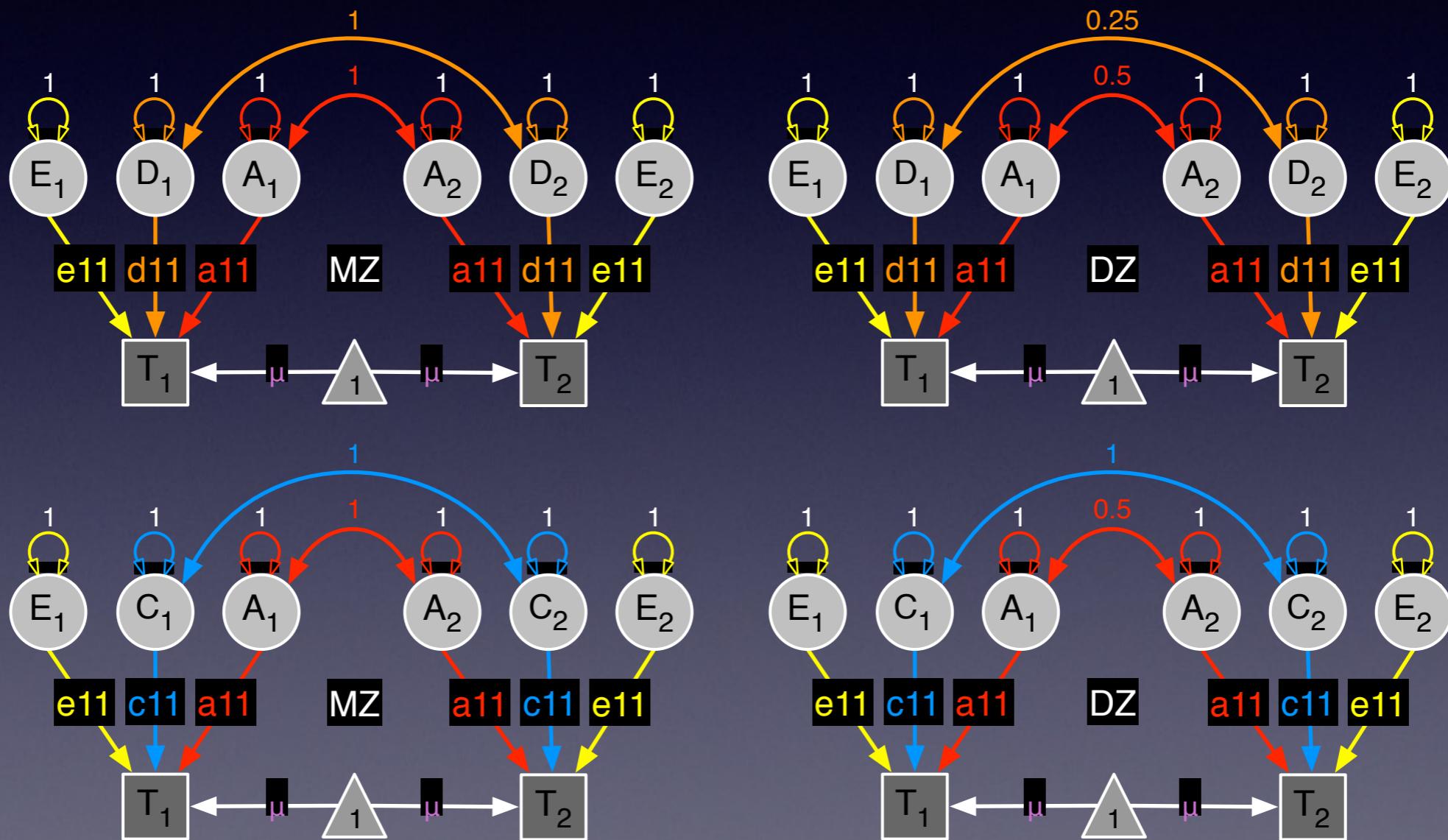
rMZ > 1/2 rDZ

A & D

Twin Correlations



Univariate ADE / ACE Model



Univariate Analysis

A Roadmap

- I. Use data to test basic assumptions (equal means & variances for twin 1/twin 2 and MZ/DZ pairs)
 - Saturated Model
2. Estimate contributions of genetic/environmental effects on total variance of a phenotype
 - ACE or ADE Models
3. Test ACE (ADE) submodels to identify and report significant genetic and environmental contributions
 - AE or CE or E Only Models

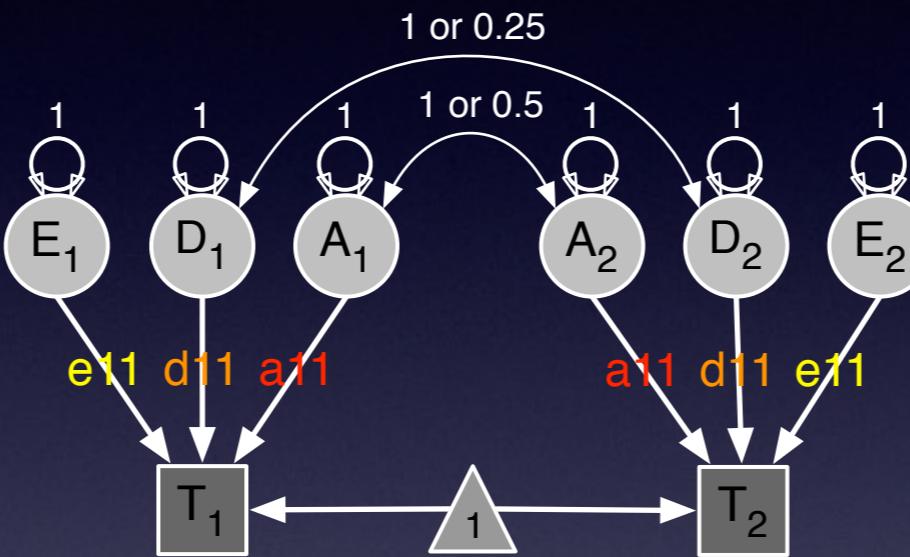
Paths & Variance Components

twinAdeCon.R [3]

```
# -----  
# PREPARE MODEL  
  
# Set Starting Values  
svMe      <- 20                      # start value for means  
svPa      <- .6                       # start value for path coefficients  
(sqrt(variance/#ofpaths))  
  
# ADE Model  
# Matrices declared to store a, d, and e Path Coefficients  
pathA     <- mxMatrix( type="Full", nrow=nv, ncol=nv, free=TRUE, values=svPa,  
label="a11", name="a" )  
pathD     <- mxMatrix( type="Full", nrow=nv, ncol=nv, free=TRUE, values=svPa,  
label="d11", name="d" )  
pathE     <- mxMatrix( type="Full", nrow=nv, ncol=nv, free=TRUE, values=svPa,  
label="e11", name="e" )  
  
# Matrices generated to hold A, D, and E computed Variance Components  
covA     <- mxAlgebra( expression=a %*% t(a), name="A" )  
covD     <- mxAlgebra( expression=d %*% t(d), name="D" )  
covE     <- mxAlgebra( expression=e %*% t(e), name="E" )
```

ADE Deconstructed

Path Coefficients



```
pathA <- mxMatrix( type="Full", nrow=nv, ncol=nv,  
free=TRUE, values=svPa, label="a11", name="a" )
```

all
a / x /

```
pathD <- mxMatrix( type="Full", nrow=nv, ncol=nv,  
free=TRUE, values=svPa, label="d11", name="d" )
```

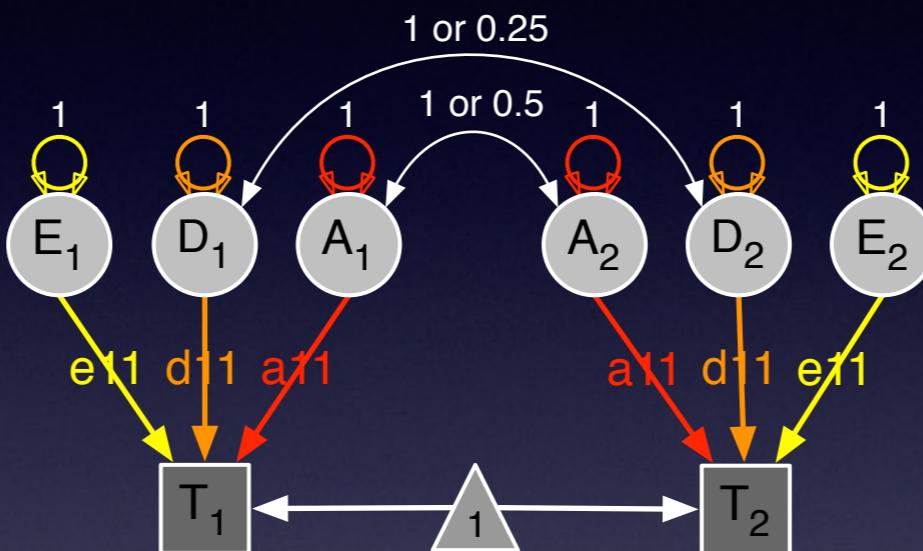
all
d / x /

```
pathE <- mxMatrix( type="Full", nrow=nv, ncol=nv,  
free=TRUE, values=svPa, label="e11", name="e" )
```

all
e / x /

ADE Deconstructed

Variance Components



```
covA      <- mxAlgebra( expression=a %*% t(a),
  name="A" )
```

$$\boxed{a} \mathbf{l} \mathbf{l} * \boxed{a} \mathbf{l} \mathbf{l}^T$$

$$A_{l \times l}$$

```
covD      <- mxAlgebra( expression=d %*% t(d),
  name="D" )
```

$$\boxed{d} \mathbf{l} \mathbf{l} * \boxed{d} \mathbf{l} \mathbf{l}^T$$

$$D_{l \times l}$$

```
covE      <- mxAlgebra( expression=e %*% t(e),
  name="E" )
```

$$\boxed{e} \mathbf{l} \mathbf{l} * \boxed{e} \mathbf{l} \mathbf{l}^T$$

$$E_{l \times l}$$

Expected Means & (Co)Variances

twinAdeCon.R [4]

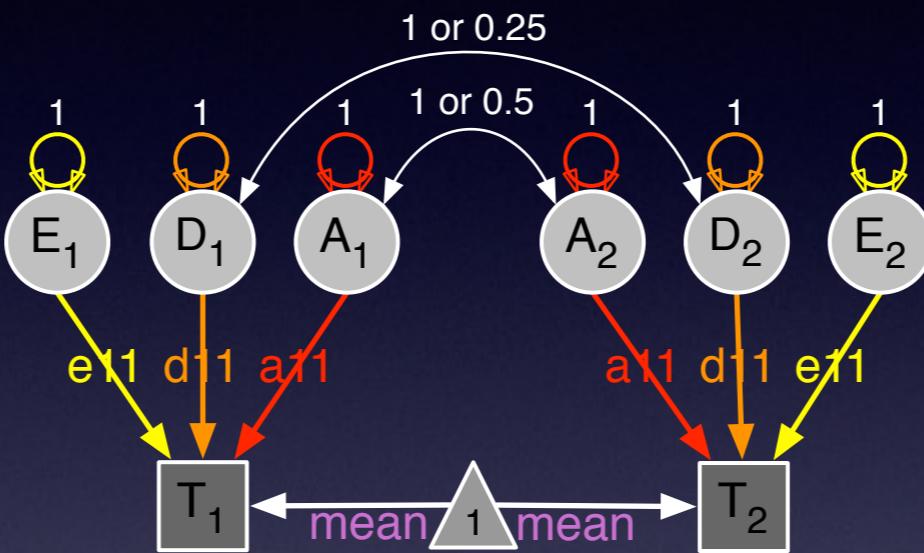
```
# Matrices for covariates and linear regression coefficients
defAge    <- mxMatrix( type="Full", nrow=1, ncol=1, free=FALSE,
                     labels=c("data.age"), name="Age")
pathB     <- mxMatrix( type="Full", nrow=1, ncol=1, free=TRUE,
                     values= .01, label="l11", name="b" )

# Algebra for expected Mean Matrices in MZ & DZ twins
meanG     <- mxMatrix( type="Full", nrow=1, ncol=ntv, free=TRUE, values=svMe,
                     labels="xbmi", name="mean" )
expMean   <- mxAlgebra( expression= mean + cbind(b%*%Age,b%*%Age),
                     name="expMean" )

# Algebra for expected Variance/Covariance Matrices in MZ & DZ twins
covP      <- mxAlgebra( expression= A+D+E, name="V" )
expCovMZ <- mxAlgebra( expression= rbind( cbind(V, A+D), cbind(A+D, V)),
                     name="expCovMZ" )
expCovDZ <- mxAlgebra( expression= rbind( cbind(V, 0.5%x%A+ 0.25%x%D),
                     cbind(0.5%x%A+ 0.25%x%D , V)), name="expCovDZ" )
```

ADE Deconstructed

Means & Variances



mean	mean
<i>expMean</i>	$l \times 2$

```
covP      <- mxAlgebra( expression= A+D+E,
name="V" )
```

```
covMZ     <- mxAlgebra( expression= rbind(
cbind(V, A+D), cbind(A+D, V)), name="expCovMZ")
```

```
covDZ     <- mxAlgebra( expression= rbind(
cbind(V, 0.5%x%A+ 0.25%x%D),
cbind(0.5%x%A+ 0.25%x%D, V)), name="expCovDZ")
```

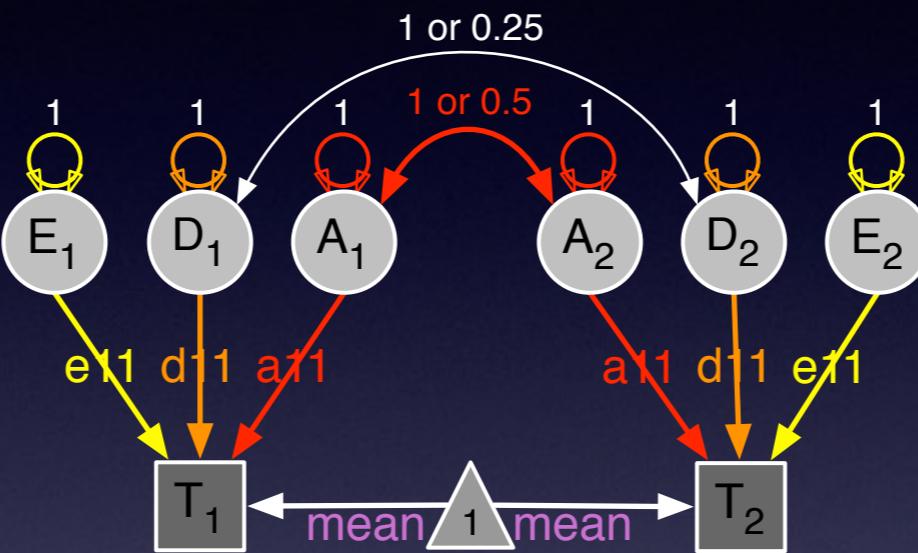
V	
	V

expCovMZ 2×2

expCovDZ 2×2

ADE Deconstructed

A Covariances



```
covP      <- mxAlgebra( expression= A+D+E,
name="V" )
```

V	A+D
A+D	V

```
covMZ     <- mxAlgebra( expression= rbind(
cbind(V, A+D), cbind(A+D, V)), name="expCovMZ")
```

expCovMZ 2×2

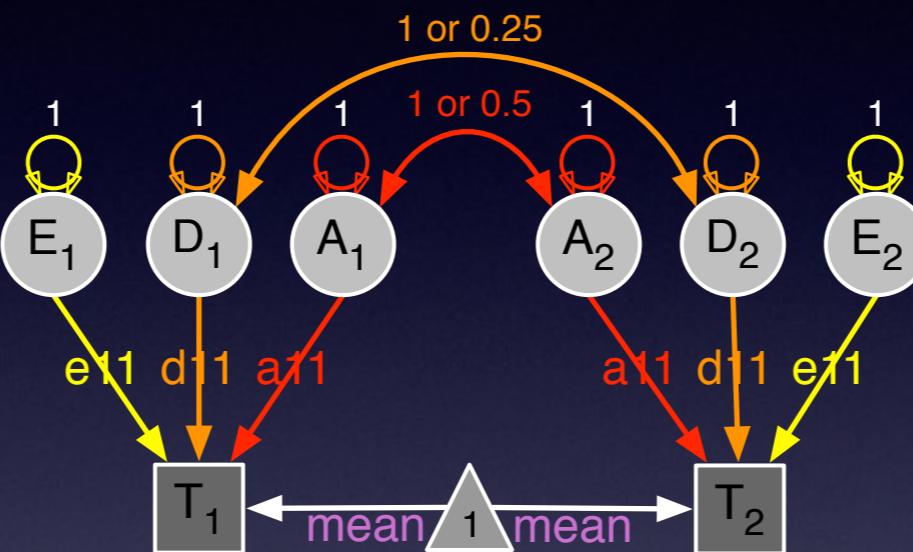
```
covDZ     <- mxAlgebra( expression= rbind(
cbind(V, 0.5%*A+ 0.25%*D),
cbind(0.5%*A+ 0.25%*D, V)), name="expCovDZ")
```

V	.5A+.25D
.5A+.25D	V

expCovDZ 2×2

ADE Deconstructed

D Covariances



```
covP      <- mxAlgebra( expression= A+D+E ,
name="V" )
```

```
covMZ     <- mxAlgebra( expression= rbind(
cbind(V, A+D), cbind(A+D, V)), name="expCovMZ")
```

```
covDZ     <- mxAlgebra( expression= rbind(
cbind(V, 0.5%*A+ 0.25%*D),
cbind(0.5%*A+ 0.25%*D, V)), name="expCovDZ")
```

V	A+D
A+D	V

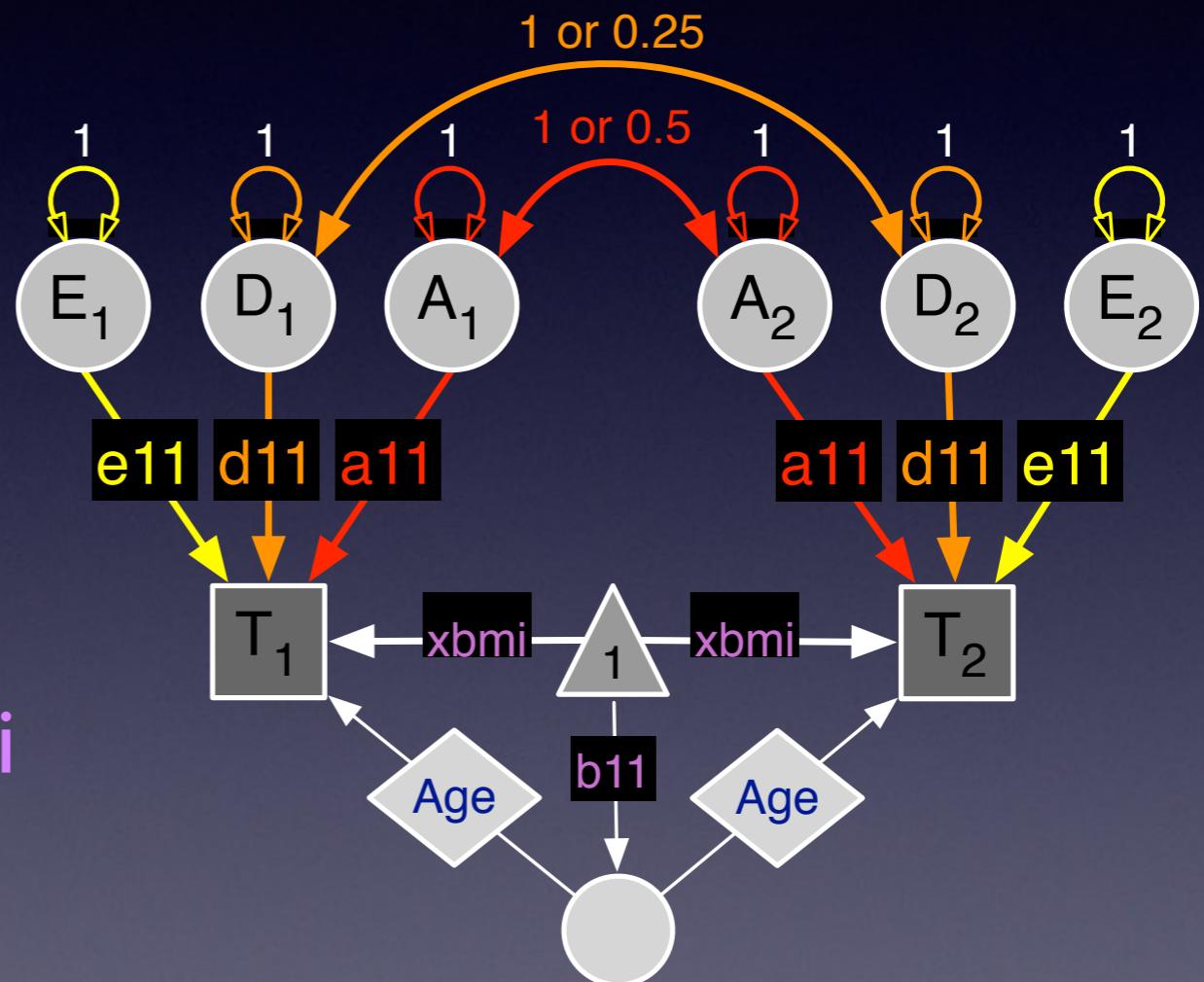
expCovMZ 2×2

V	.5A+.25D
.5A+.25D	V

expCovDZ 2×2

ADE Deconstructed Parameters

5 Parameters Estimated:
Mean xbmi
Regression on Age b_{11}
Variance due to A a_{11}
Variance due to D d_{11}
Variance due to E e_{11}



Data & Objectives

twinAdeCon.R [5]

```
# Data objects for Multiple Groups
dataMZ    <- mxData( observed=mzData, type="raw" )
dataDZ    <- mxData( observed=dzData, type="raw" )

# Objective objects for Multiple Groups
objMZ     <- mxFIMLObjective( covariance="expCovMZ", means="expMean",
                               dimnames=selVars )
objDZ     <- mxFIMLObjective( covariance="expCovDZ", means="expMean",
                               dimnames=selVars )

# Combine Groups
pars       <- list( pathA, pathD, pathE, covA, covD, covE, covP, pathB )
modelMZ   <- mxModel( pars, defAge, meanG, expMean, expCovMZ, dataMZ, objMZ,
                      name="MZ" )
modelDZ   <- mxModel( pars, defAge, meanG, expMean, expCovDZ, dataDZ, objDZ,
                      name="DZ" )
minus2ll  <- mxAlgebra( expression=MZ.objective + DZ.objective, name="m2LL" )
obj       <- mxAlgebraObjective( "m2LL" )
AdeModel  <- mxModel( "ADE", pars, modelMZ, modelDZ, minus2ll, obj )
```

Model Fitting

twinAdeCon.R [6]

```
# RUN MODEL

# Run ADE model
AdeFit      <- mxRun(AdeModel, intervals=T)
AdeSumm     <- summary(AdeFit)
AdeSumm
mxCompare(twinSatFit,AdeFit)
round(AdeFit@output$estimate,4)
round(AdeFit$Vars@result,4)

# Generate Table of Parameter Estimates using mxEval
pathEstimatesADE   <- print(round(mxEval(cbind(a,d,e), AdeFit),4))
varComponentsADE <- print(round(mxEval(cbind(A/V,D/V,E/V), AdeFit),4))
rownames(pathEstimatesADE) <- 'pathEstimates'
colnames(pathEstimatesADE) <- c('a','d','e')
rownames(varComponentsADE) <- 'varComponents'
colnames(varComponentsADE) <- c('a^2','d^2','e^2')
pathEstimatesADE
varComponentsADE
```

Generating Output

twinAdeCon.R [7]

```
# Generate ADE Model Output
estMean    <- mxEval(expMean, AdeFit$MZ)      # expected mean
estCovMZ   <- mxEval(expCovMZ, AdeFit$MZ)     # expected covariance matrix for MZ's
estCovDZ   <- mxEval(expCovDZ, AdeFit$DZ)     # expected covariance matrix for DZ's
estVA      <- mxEval(a*a, AdeFit)                # additive genetic variance, a^2
estVD      <- mxEval(d*d, AdeFit)                # dominance variance, d^2
estVE      <- mxEval(e*e, AdeFit)                # unique environmental variance, e^2
estVP      <- (estVA+estVD+estVE)               # total variance
estPropVA <- estVA/estVP                         # standardized additive genetic variance
estPropVD <- estVD/estVP                         # standardized dominance variance
estPropVE <- estVE/estVP                         # standardized unique environmental var
estADE     <- rbind(cbind(estVA,estVD,estVE),    # table of estimates
                    cbind(estPropVA,estPropVD,estPropVE))
LL_ADE    <- mxEval(objective, AdeFit)          # likelihood of ADE model
```

summary(mxModel)

free parameters:

	name	matrix	row	col	Estimate	Std.Error	lbound	ubound
1	a11	a	1	1	0.6060900		NaN	
2	d11	d	1	1	0.4743898		NaN	
3	e11	e	1	1	0.4111268		NaN	
4	l11	b	1	1	2.7677606		NaN	
5	xbmi	MZ.mean	1	1	20.7346094		NaN	

confidence intervals:

	lbound	estimate	ubound
ADE.Vars[1,1]	6.811043e-02	0.3673451	0.6333987
ADE.Vars[1,2]	5.966440e-21	0.2250457	0.5243742
ADE.Vars[1,3]	1.502990e-01	0.1690253	0.1909726
ADE.Vars[1,4]	8.988222e-02	0.4824499	0.7934488
ADE.Vars[1,5]	1.415784e-13	0.2955620	0.6894092
ADE.Vars[1,6]	1.937827e-01	0.2219881	0.2545650

observed statistics: 1775

estimated parameters: 5

degrees of freedom: 1770

-2 log likelihood: 4022.789

number of observations: 919

Information Criteria AIC: 1832.789

Goodness-of-Fit Stats

	ep	-2ll	df	AIC	diff -2ll	diff df	P
Saturated	11	4015.12	1764	487.12			
ADE	5	4022.79	1770	482.79	7.67	6	0.26

Table of Estimates

```
> # Generate Table of Parameter Estimates using mxEval  
> pathEstimatesADE  
          a      d      e  
pathEstimates 0.6061 0.4744 0.4111  
> varComponentsADE  
          a^2     d^2     e^2  
varComponents 0.4824 0.2956 0.222
```

Univariate Analysis

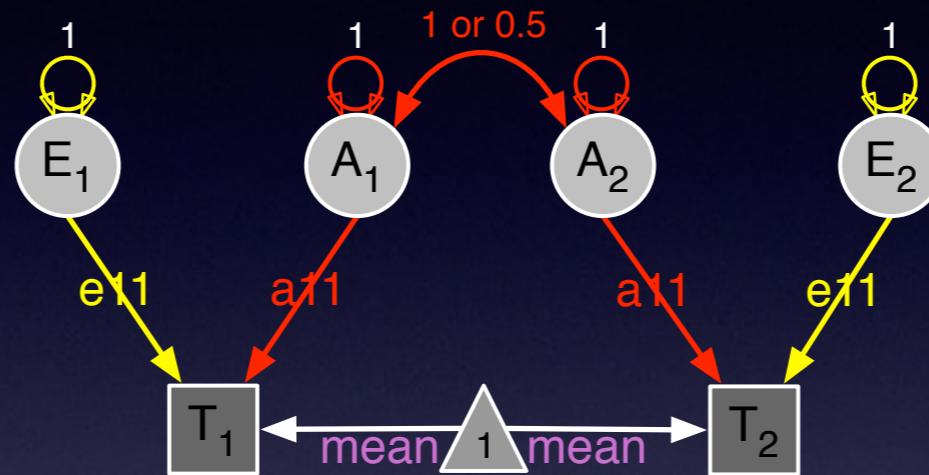
A Roadmap

- I. Use data to test basic assumptions (equal means & variances for twin 1/twin 2 and MZ/DZ pairs)
 - Saturated Model
2. Estimate contributions of genetic/environmental effects on total variance of a phenotype
 - ACE or ADE Models
3. Test ACE (ADE) submodels to identify and report significant genetic and environmental contributions
 - AE or CE or E Only Models

Nested Models

- ‘Full’ ADE Model
- Nested Models
 - AE Model
 - test significance of D
 - E Model vs AE Model
 - test significance of A
 - E Model vs ADE Model
 - test combined significance of A & D

AE Deconstructed Parameters



```
# Test significance of D
# Copy model, provide new name
AeModel <- mxModel(AdeFit, name="AE")

# Change parameter by changing attributes for label
AeModel <- omxSetParameters( AeModel,
  label="d11", free=FALSE, values=0 )

# Fit Nested Model
AeFit <- mxRun(AeModel)

# Compare Nested Model with 'Full' Model
mxCompare(AdeFit, AeFit)
```

AE Model

twinAdeCon.R [8]

```
# -----
# FIT SUBMODELS

# Run AE model
AeModel    <- mxModel( AdeFit, name="AE" )
AeModel    <- omxSetParameters( AeModel, labels="d11", free=FALSE, values=0 )
AeFit      <- mxRun(AeModel)
mxCompare(AdeFit, AeFit)
round(AeFit$output$estimate,4)
round(AeFit$Vars$result,4)

# Run E model
eModel    <- mxModel( AeFit, name="E" )
eModel    <- omxSetParameters( eModel, labels="a11", free=FALSE, values=0 )
eFit      <- mxRun(eModel)
mxCompare(AeFit, eFit)
round(eFit$output$estimate,4)
round(eFit$Vars$result,4)

# Print Comparative Fit Statistics
AdeNested <- list(AeFit, eFit)
mxCompare(AdeFit,AdeNested)
round(rbind(AdeFit$Vars$result,AeFit$Vars$result,eFit$Vars$result),4)
```

Goodness-of-Fit Statistics

	ep	-2II	df	AIC	diff -2II	diff df	P
ADE							
AE							
E							

Estimated Values

Goodness-of-Fit Statistics

	ep	-2II	df	AIC	diff -2II	diff df	P
ADE	5	4022.79	1770	482.79			
AE	4	4025.41	1771	483.41	2.62	1	0.10
E	3	4549.61	1772	1005.61	526.8	2	0

Estimated Values

	path coefficients			unstandardized variance components			standardized variance components		
	a	d	e	a^2	d^2	e^2	a^2	d^2	e^2
ADE	0.61	0.47	0.41	0.37	0.25	0.17	0.48	0.30	0.22
AE	0.77	-	0.41	0.60	-	0.17	0.77	-	0.22
E	-	-	0.87	-	-	0.76	-	-	1.00

What about C?

- ‘Full’ ACE Model
- Nested Models
 - AE Model
 - test significance of C
 - CE Model
 - test significance of A
 - E Model vs AE Model
 - test significance of A
 - E Model vs ACE Model
 - test combined significance of A & C

Goodness-of-Fit Statistics

	ep	-2II	df	AIC	diff -2II	diff df	P
ADE							
AE							
ACE							
CE							
E							

Estimated Values

	a	d	e	c	a^2	d^2	e^2	c^2
ADE								
AE								
ACE								
AE								
E								

Conclusions

- BMI in young OZ females (age 18-30)
 - additive genetic factors: highly significant
 - dominance: borderline non-significant
 - specific environmental factors: significant
 - shared environmental factors: not