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Overview

 Psychiatric Disorders: binary phenotypes - Lots of comorbidity - Substance abuse similar ACE model is but one of many Two twins, two binary variables – 16 outcome combinations Fit models by maximum likelihood - (alternatives exist)

Assessment of Psychiatric Disorders

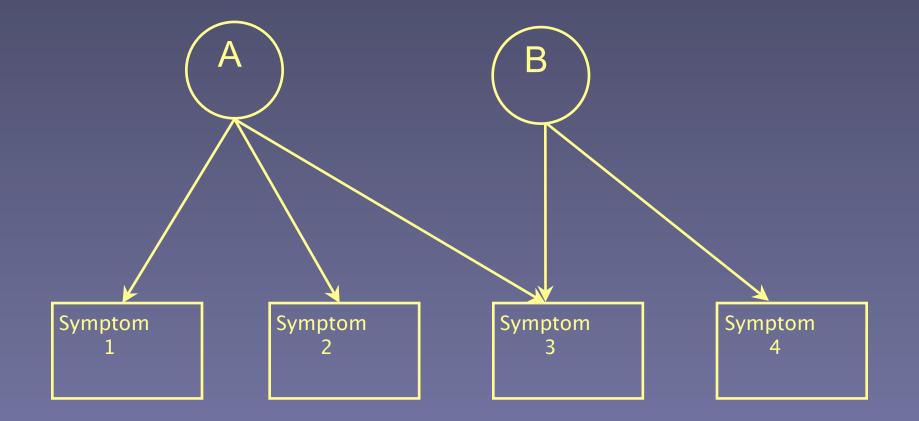
- Psychiatrists can agree on symptoms better than on diagnoses (Kendell et al 1971)
- Diagnostic and Statistical Manual of Mental Disorders (DSM-III 1980; DSM-IIIR 1987; DSM-IV 1994; DSM-IV 2012). Widespread use
- Little empirical basis for classification
- "If you believe..."

Comorbidity is High

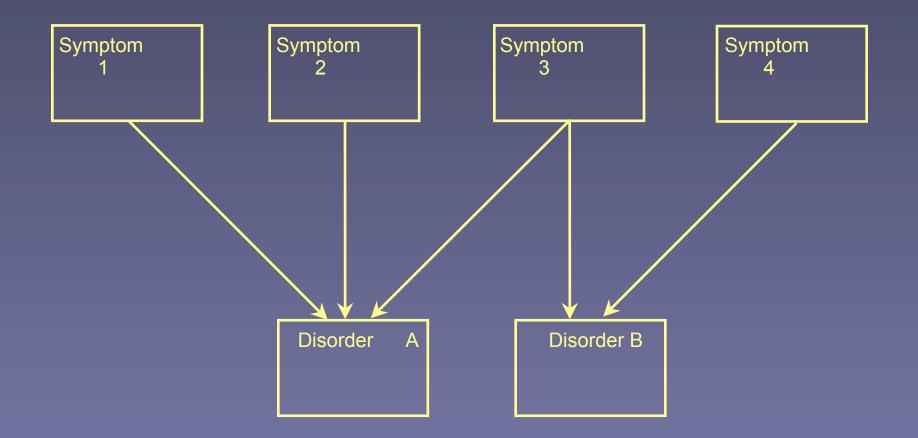
High for Psychiatric Disorders

- Anxiety
- Depression
- Phobias
- Panic
- Alcohol Abuse
- 70% of those with history of 1 have history of at least one other (Kessler 1993; N=18,000)
- Similar rates in 10,000+ Virginia twins

Pure forms of two disorders A & B generate some of the same symptoms

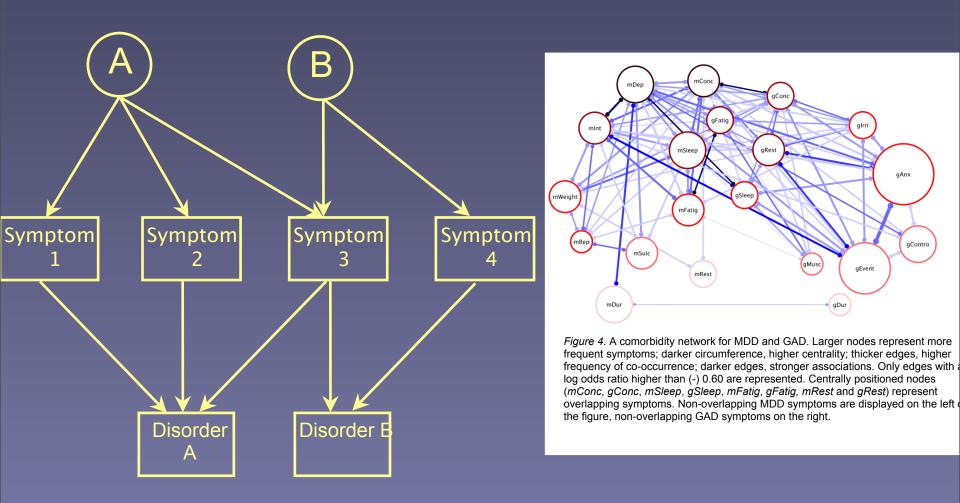


Assessments of disorders A & B share some symptoms



Cramer, Waldrop, Van der Maas, Borsboom (In Press) Comorbidity: A network perspective. Brain Behavior Sciences

Comorbidity due to symptom sharing



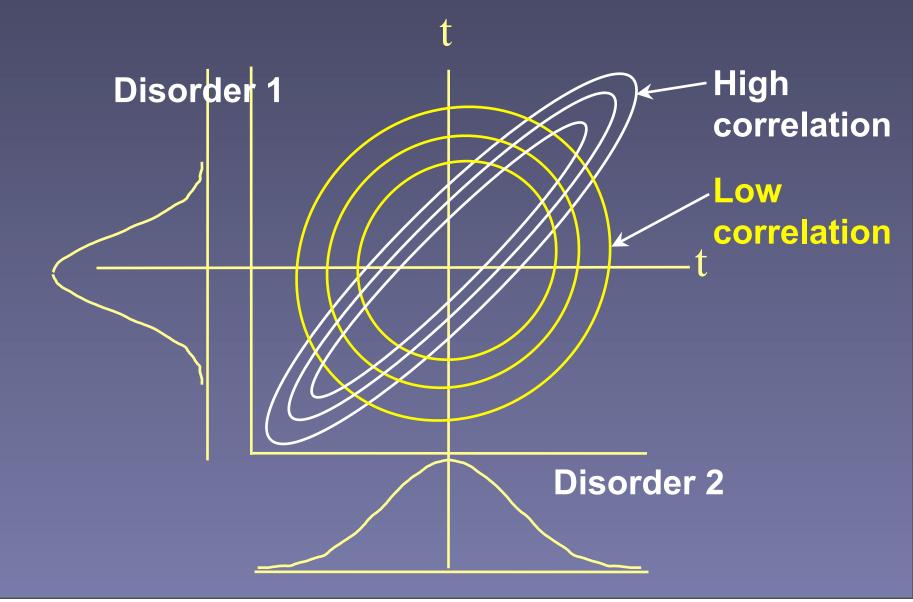
Not today!

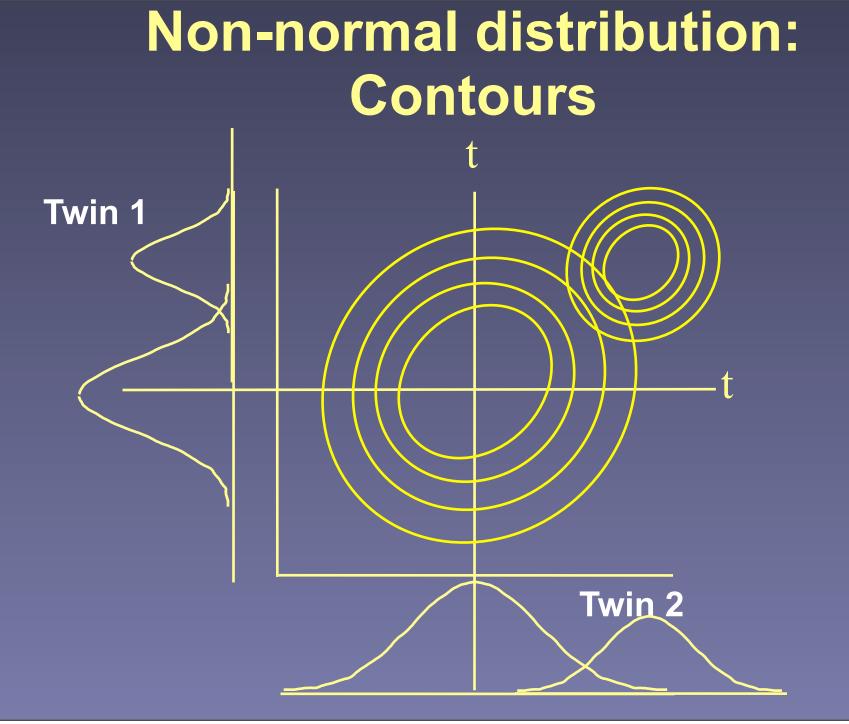
Why do people get a disorder? Single factor of large effect? Lots of little factors of cumulative effect? Both?

How do we find out which? Measure variation Measure covariation to understand it

Basic statistical theory

Two Dimensions: Contours





Basic Theory

- Models for symptoms:
 - Latent class analysis
 - Factor analysis
 - Factor mixture model
 - Reprieved...

Am. J. Hum. Genet. 57:935-953, 1995

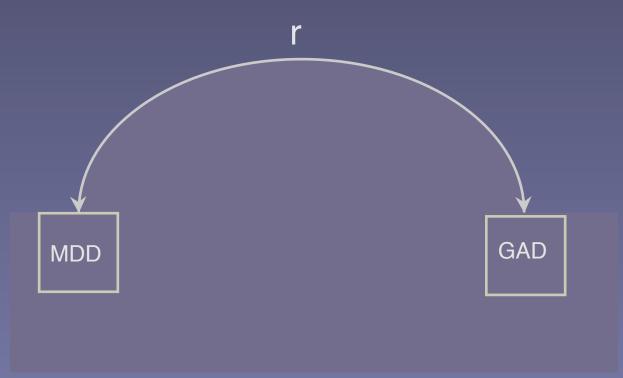
Models of Comorbidity for Multifactorial Disorders

Michael C. Neale' and Kenneth S. Kendler^{1,2}

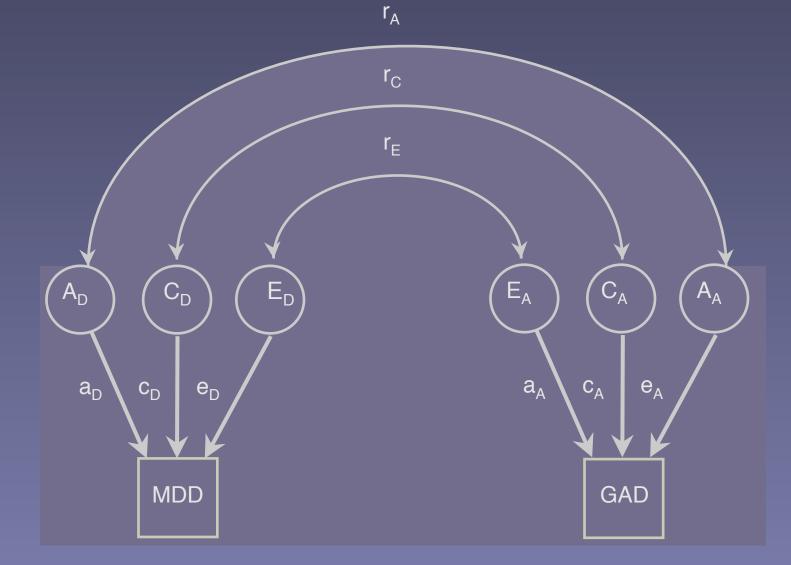
Departments of 'Psychiatry and 'Human Genetics, Medical College of Virginia, Richmond

Comorbidity

A correlation between (binary) traits Neale & Kendler (1995) 13 Models Based on Klein & Riso (1994)

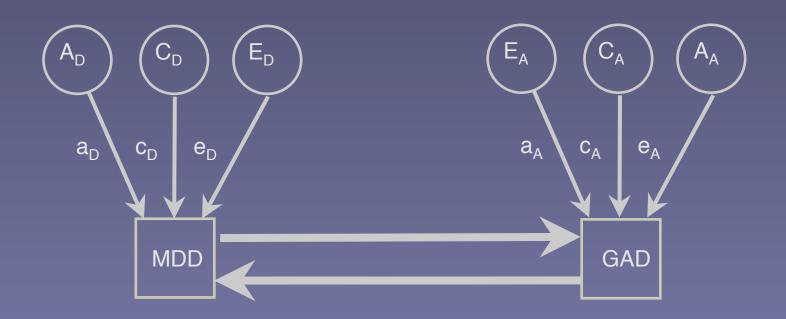


Partitioning Comorbidity



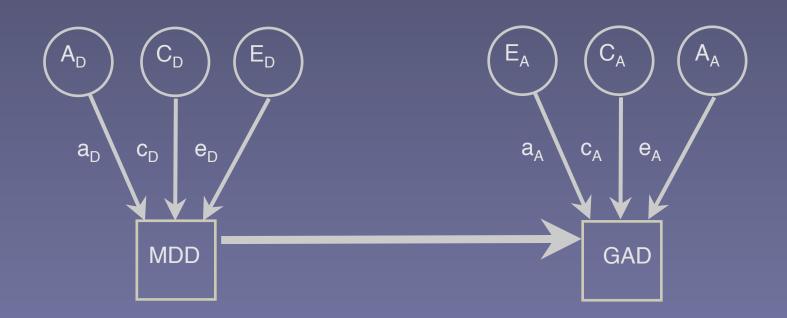
Modeling Comorbidity

Reciprocal Causation



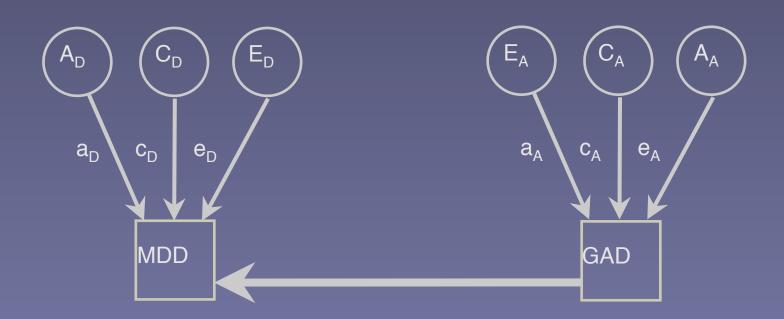
Modeling Comorbidity

Major Depression Causes Generalized Anxiety Disorder



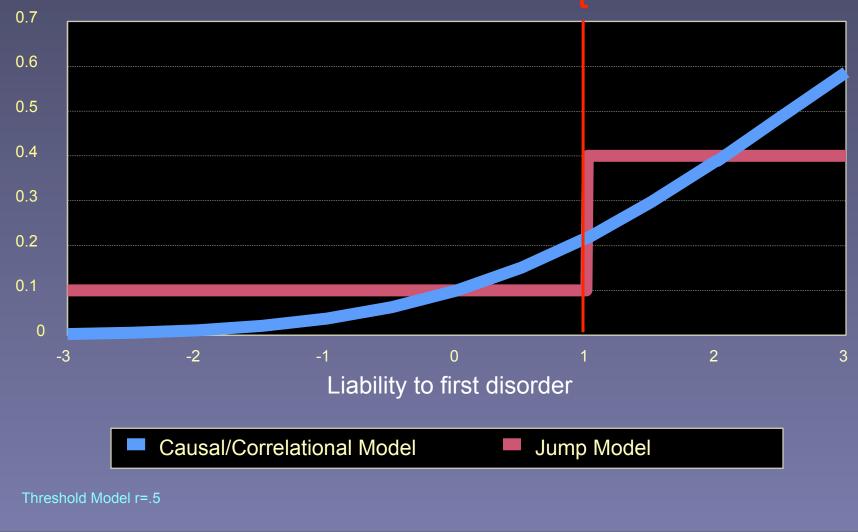
Modeling Comorbidity

Generalized Anxiety Disorder causes Major Depression

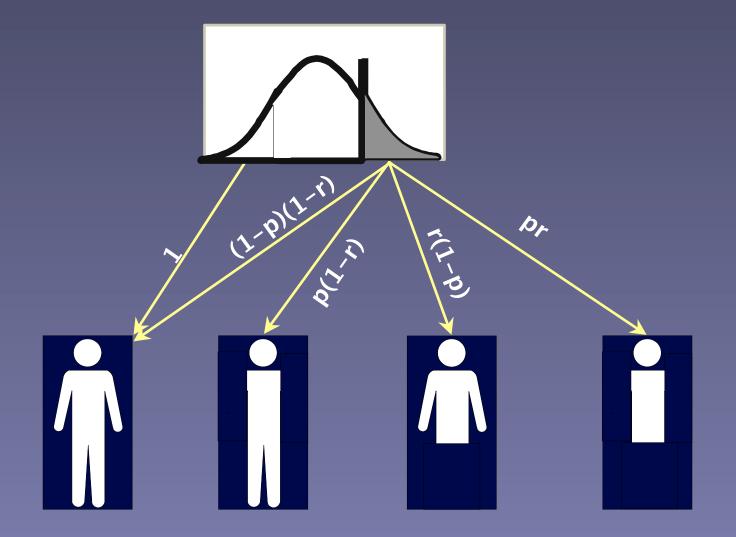


Alternative models of increasing risk to a second disorder

p(comorbid) = chance of getting second disorder



Alternate forms: One underlying continuum



Alternate forms: More detail

$$L = \int_{-\infty}^{t_1} \phi(R) dR \qquad (1)$$

$$M = \int_{t_1}^{t_2} \phi(R) dR \tag{2}$$

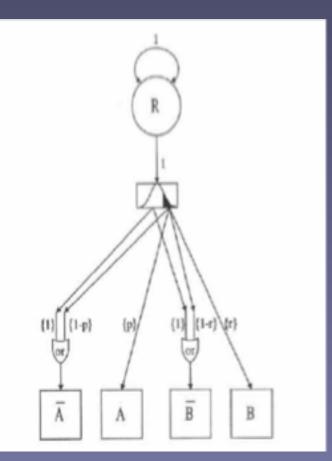
$$U = \int_{t_2}^{\infty} \phi(R) dR . \qquad (3)$$

$$P(\bar{A}, \bar{B}) = L + (1 - p)(1 - r)U$$
 (4)

 $P(\overline{A}, B) = p(1 - r)U \qquad (5)$

$$P(\mathbf{A}, \mathbf{\overline{B}}) = (1 - p)rU \tag{6}$$

$$P(A, B) = prU$$
, (7)



Alternate forms: Detail of pairs

$$LL_{\rm A} = \int_{-\infty}^{c_{\rm A}} \int_{-\infty}^{c_{\rm A}} \phi(R_{\rm A3}, R_{\rm A2}) dR_{\rm A2} dR_{\rm A3} \qquad (24)$$

$$LM_{\rm A} = \int_{-\infty}^{c_{\rm A}} \int_{r_{\rm A}}^{r_{\rm A}} \phi(R_{\rm A1}, R_{\rm A2}) dR_{\rm A2} dR_{\rm A1}$$
 (25)

$$LU_{A} = \int_{-\infty}^{c_{1_{A}}} \int_{C_{A}}^{\infty} \phi(R_{A1}, R_{A2}) dR_{A2} dR_{A1} \qquad (26)$$

$$MM_{\rm A} = \int_{t1_{\rm A}}^{t2_{\rm A}} \int_{t1_{\rm A}}^{t2_{\rm A}} \phi(R_{\rm A1}, R_{\rm A2}) dR_{\rm A2} dR_{\rm A3} \qquad (27)$$

$$MU_{\rm A} = \int_{t1_{\rm A}}^{t2_{\rm A}} \int_{t1_{\rm A}}^{tt} \phi(R_{\rm A1}, R_{\rm A2}) dR_{\rm A2} dR_{\rm A1} \qquad (28)$$

$$UU_{\rm A} = \int_{\alpha_{\rm A}}^{\infty} \int_{\alpha_{\rm A}}^{\infty} \phi(R_{\rm A1}, R_{\rm A2}) dR_{\rm A2} dR_{\rm A1} , \quad (29)$$

$$P(A1, B1, A2, B2) = p^2 r(1 - r) UU$$
 (38)

$$P(A1, B1, A2, B2) = p^2 r^2 UU$$
. (39)

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = LL + 2(1 - p)(1 - r)UL + (1 - p)^{2}(1 - r)^{2}UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = r(1 - p)LU + (1 - p)^{2}r(1 - r)^{2}UU$$

$$P(\bar{A}1, \bar{B}1, A2, \bar{B}2) = p(1 - r)LU + p(1 - p)(1 - r)^{2}UU$$

$$P(\bar{A}1, \bar{B}1, A2, \bar{B}2) = prLU + p(1 - p)r(1 - r)UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = (1 - p)^{2}r^{2}UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r(1 - r)UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r(1 - r)UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r(1 - r)UU$$

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$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r(1 - r)UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r(1 - r)UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r^{2}UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r(1 - r)UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r^{2}UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p(1 - p)r^{2}UU$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = p^{2}(1 - r)^{2}UU$$

Program: Alternate Forms

```
require(OpenMx)
nv < -1
# Fit Alternate Forms Model with Cell Frequencies Input, ACE.one overall Threshold
#
AltFormsModel <- mxModel("AlternateForms",</pre>
    mxModel("ACE",
    # Matrices a, c, and e to store a, c, and e path coefficients
        mxMatrix( type="Full", nrow=nv, ncol=nv, free=TRUE, values=.6, label="a11",
name="a"),
        mxMatrix( type="Full", nrow=nv, ncol=nv, free=TRUE, values=.6, label="c11",
name="c").
        mxMatrix( type="Full", nrow=nv, ncol=nv, free=TRUE, values=sqrt(.28), label="e11",
name="e"),
    # Matrices A, C, and E compute variance components
        mxAlgebra( expression=a %*% t(a), name="A" ),
        mxAlgebra( expression=c %*% t(c), name="C" ),
        mxAlgebra( expression=e %*% t(e), name="E" ),
    # Algebra to compute total variances and standard deviations (diagonal only)
        mxAlgebra( expression=A+C+E, name="V" ),
        mxMatrix( type="Iden", nrow=nv, ncol=nv, name="I"),
        mxAlgebra( expression=solve(sqrt(I*V)), name="sd"),
    # Constraint on variance of A+C+E latent variables
        mxConstraint( alg1="V", "=", alg2="I", name="Var1"),
```

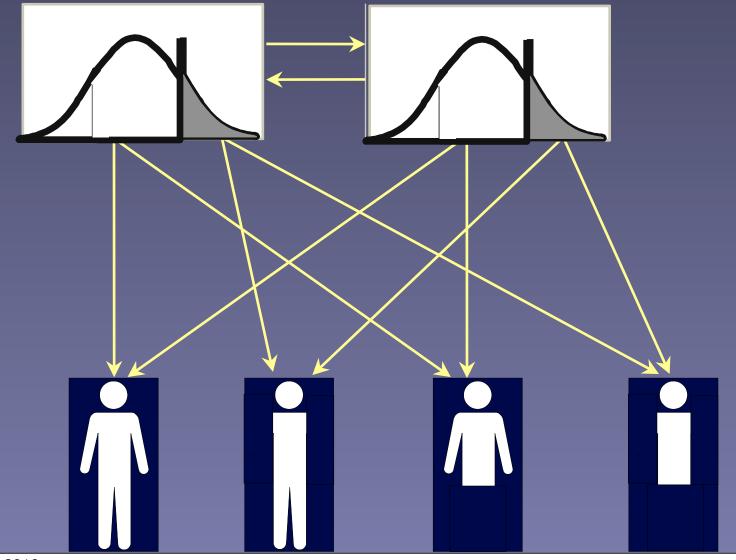
Algebra for expected variance/covariance matrix in MZ
<pre>mxAlgebra(expression= rbind (cbind(A+C+E , A+C),</pre>
<pre>cbind(A+C , A+C+E)), name="expCovMZ"),</pre>
Algebra for expected variance/covariance matrix in DZ, note use of 0.5,
<pre>mxAlgebra(expression= rbind (cbind(A+C+E , 0.5%x%A+C),</pre>
<pre>cbind(0.5%x%A+C , A+C+E)), name="expCovDZ"),</pre>
Matrices for probabilities P Q R S of being affected given below/above threshold
mxMatrix(type="Full", nrow=1, ncol=1, free=TRUE, values=.8, label="p", name="P"),
<pre>mxMatrix(type="Full", nrow=1, ncol=1, free=TRUE, values=.6, label="r", name="R"),</pre>
<pre>mxMatrix(type="Iden", nrow=1, ncol=1, free=F, name="I"),</pre>
<pre>mxAlgebra(expression= I-P, name="Q"),</pre>
<pre>mxAlgebra(expression= I-R, name="S"),</pre>
Threshold parameter & matrices for (fixed at zero) means
<pre>mxMatrix(type="Full", nrow=1, ncol=1, free=TRUE, values=1, label="tmz", name="T"),</pre>
<pre>mxMatrix(type="Zero", nrow=1, ncol=nv, name="M"),</pre>
<pre>mxAlgebra(expression= cbind(M,M), name="expMean"),</pre>
Integrals for computing the pairwise probabilities of being above/below threshold - MZ
<pre>mxAlgebra(expression=omxMnor(expCovMZ, expMean, cbind(-Inf,-Inf), cbind(T,T)),</pre>
name="bothBelow"),
<pre>mxAlgebra(expression=omxMnor(expCovMZ, expMean, cbind(-Inf,T), cbind(T,Inf)),</pre>
name="oneBelow"),
<pre>mxAlgebra(expression=omxMnor(expCovMZ, expMean, cbind(T,T), cbind(Inf,Inf)),</pre>
name="bothAbove"),

```
# Integrals for computing the pairwise probabilities of being above/below threshold - DZ
mxAlgebra(expression=omxMnor(expCovDZ, expMean, cbind(-Inf,-Inf), cbind(T,T)),
name="bothBelowDZ"),
mxAlgebra(expression=omxMnor(expCovDZ, expMean, cbind(-Inf,T), cbind(T,Inf)),
name="oneBelowDZ"),
mxAlgebra(expression=omxMnor(expCovDZ, expMean, cbind(T,T), cbind(Inf,Inf)),
name="bothAboveDZ"),
```

```
# Finally, predicted proportions in each of 10 cells for MZ
mxAlgebra(rbind(
    bothBelow + 2*oneBelow*Q*S + bothAbove*Q*Q*S*S,
    2*(oneBelow*R*Q + bothAbove*Q*Q*R*S),
    2*(oneBelow*P*S + bothAbove*P*Q*S*S),
    2*(oneBelow*P*R + bothAbove*P*R*Q*S),
    bothAbove*Q*Q*R*R,
    2*bothAbove*P*Q*R*S,
    2*bothAbove*P*Q*R*S,
    2*bothAbove*P*Q*R*S,
    2*bothAbove*P*S*P*S,
    2*bothAbove*P*S*P*R,
    bothAbove*P*R*P*R
    ),name="MZExpectedFrequencies"),
```

```
# Finally, predicted proportions in each of 10 cells for DZ
   mxAlgebra(rbind(
   bothBelowDZ + 2*oneBelowDZ*Q*S + bothAboveDZ*Q*Q*S*S,
   2*(oneBelowDZ*R*Q + bothAboveDZ*Q*Q*R*S),
    2*(oneBelowDZ*P*S + bothAboveDZ*P*Q*S*S),
   2*(oneBelowDZ*P*R + bothAboveDZ*P*R*Q*S),
   bothAboveDZ*0*0*R*R.
   2*bothAboveDZ*P*O*R*S.
   2*bothAboveDZ*P*Q*R*R,
   bothAboveDZ*P*S*P*S.
    2*bothAboveDZ*P*S*P*R.
   bothAboveDZ*P*R*P*R),name="DZExpectedFrequencies")),
mxModel("MZ",
   mxMatrix(type="Full", nrow=10, ncol=1, free=FALSE,
      values=c(141,35,32,25,15,7,33,18,39,47), name="MZObservedFrequencies"),
    mxAlgebra( -2 * sum(MZObservedFrequencies * log
              (ACE.MZExpectedFrequencies)),name="MZalqobj"),
mxAlgebraObjective("MZalgobj")),
```

Causal or correlated models



Correlated Liabilities

P(A1, B1, A2, B2)

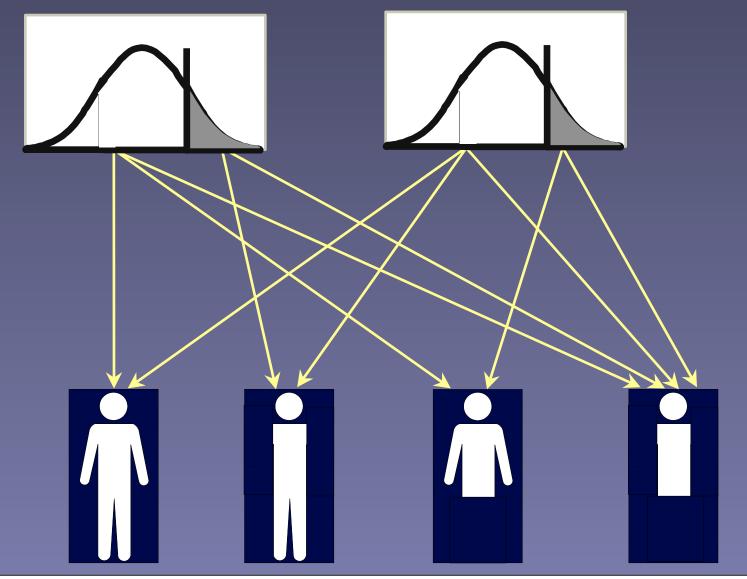


$= \int_{t_{\rm A}}^{\infty} \int_{t_{\rm B}}^{\infty} \int_{t_{\rm A}}^{\infty} \int_{t_{\rm B}}^{\infty} \phi(R_{\rm A1}, R_{\rm B1}, R_{\rm A2}, R_{\rm B2})$

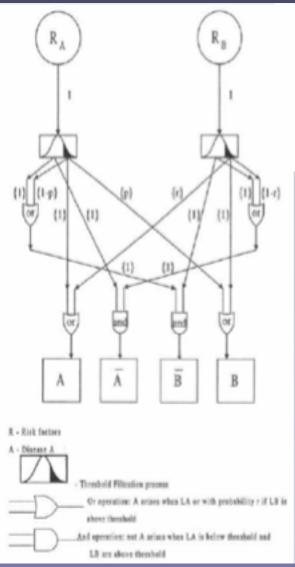
 $dR_{B2}dR_{A2}dR_{B1}dR_{A1}$

Inherent in OpenMx Ordinal Data Analysis We can do it by hand as well

Jump Model: Actually having one disorder raises chance of getting second



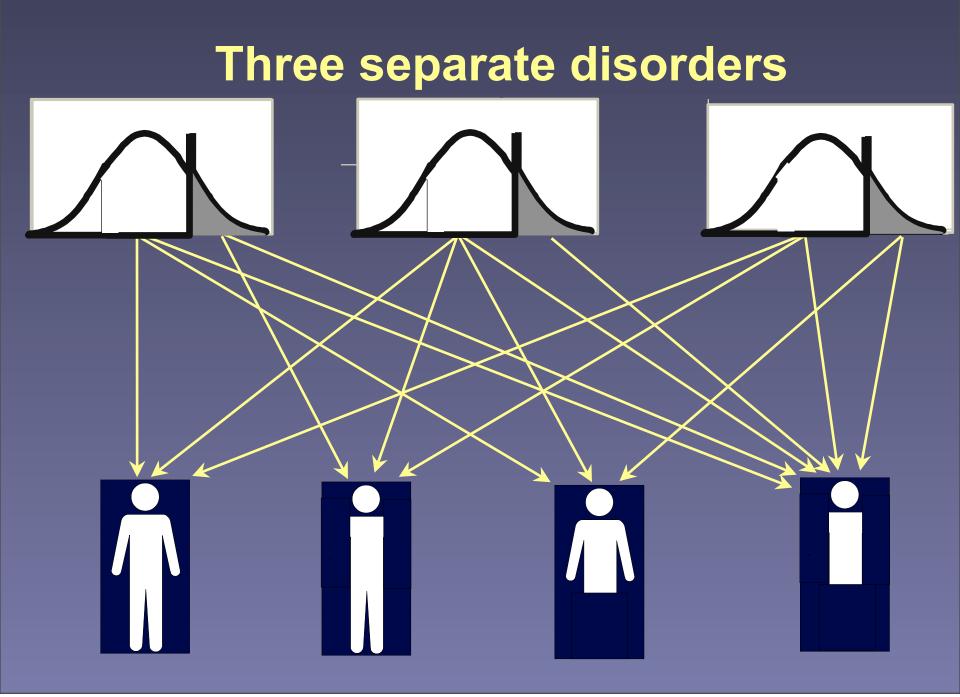
Random Multiformity: Detail



$P(\overline{A}, \overline{B}) = L_A \cdot L_B$	(8)
$P(\overline{\mathbf{A}}, \mathbf{B}) = (1 - r)L_{\mathbf{A}} \cdot U_{\mathbf{B}}$	(9)
$P(A, \overline{B}) = U_A \cdot (1 - p)L_B$	(10)

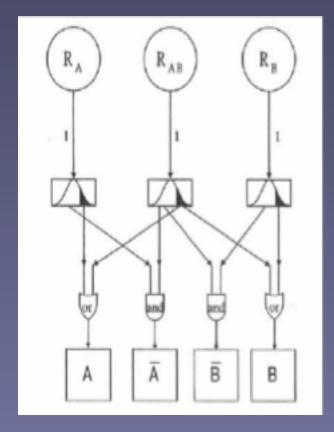
$$P(A, B) = U_A \cdot (U_B + pL_B) + rL_A \cdot U_B$$
, (11)

$P(\overline{A}1,\overline{B}1,\overline{A}2,\overline{B}2)=LL_{A}\cdot LL_{B}$	(40)	
$P(\overline{\mathrm{A}}1,\overline{\mathrm{B}}1,\overline{\mathrm{A}}2,\mathrm{B}2)=LL_{\mathtt{A}}\cdot(1-r)LU_{\mathtt{B}}$	(41)	
$P(\overline{\mathrm{A}}1,\overline{\mathrm{B}}1,\mathrm{A}2,\overline{\mathrm{B}}2) = (1-p)LU_{\mathrm{A}}\cdot LL_{\mathrm{B}}$	(42)	
$\begin{split} P(\overline{A}1,\overline{B}1,A2,B2) &= LU_{A} \cdot (pLL_{B} + LU_{B}) \\ &+ LL_{A} \cdot rLU_{B} \end{split}$	(43)	
$P(\overline{\mathrm{A}}1,\mathrm{B}1,\overline{\mathrm{A}}2,\mathrm{B}2)=LL_{\mathrm{A}}\cdot(1-r)^{2}UU_{\mathrm{S}}$	(44)	
$P(\overline{A}1, \mathbb{B}1, \mathbb{A}2, \overline{\mathbb{B}}2) = (1-p)LU_{\mathbb{A}} \cdot (1-r)LU_{\mathbb{B}}$	(45)	
$\begin{split} P(\overline{A}1, B1, A2, B2) &= (1 - r)LU_A \cdot (pLU_B + UU_B) \\ &+ LL_A \cdot rLL_B \end{split}$	(46)	
$P(A1, \overline{B1}, \operatorname{A2}, \overline{B2}) = (1-p)^2 U U_{\mathbb{A}} \cdot L L_{\mathbb{B}}$	(47)	
$\begin{split} P(\text{A1}, \text{B1}, \text{A2}, \text{B2}) &= UU_{\text{A}} \cdot (p(1-p)LL_{\text{B}} \\ &+ (1-p)LU_{\text{B}}) \\ &+ (1-p)LU_{\text{A}} \cdot rLU_{\text{B}} \end{split}$	(48)	
$P(A1, B1, A2, B2) = p^2 U U_{\Lambda} \cdot LL_n$		
$+ 2pUU_A \cdot LU_B$ $+ UU_A \cdot UU_B$		
$+ LU_{A} \cdot 2rUU_{B}$	(49)	
$+ 2pLU_{A} \cdot rLU_{B}$		
$+ LL_{\Lambda} \cdot r^2 UU_{\beta}$.		

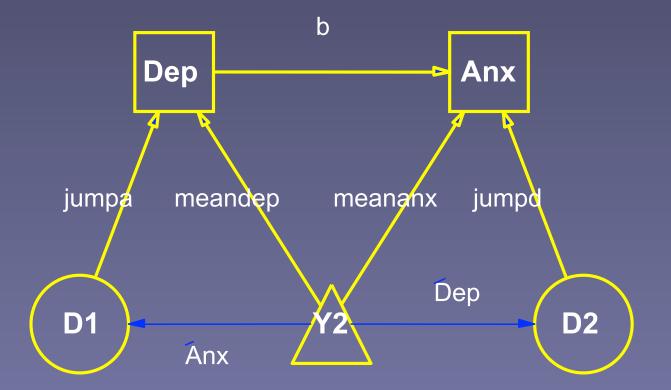


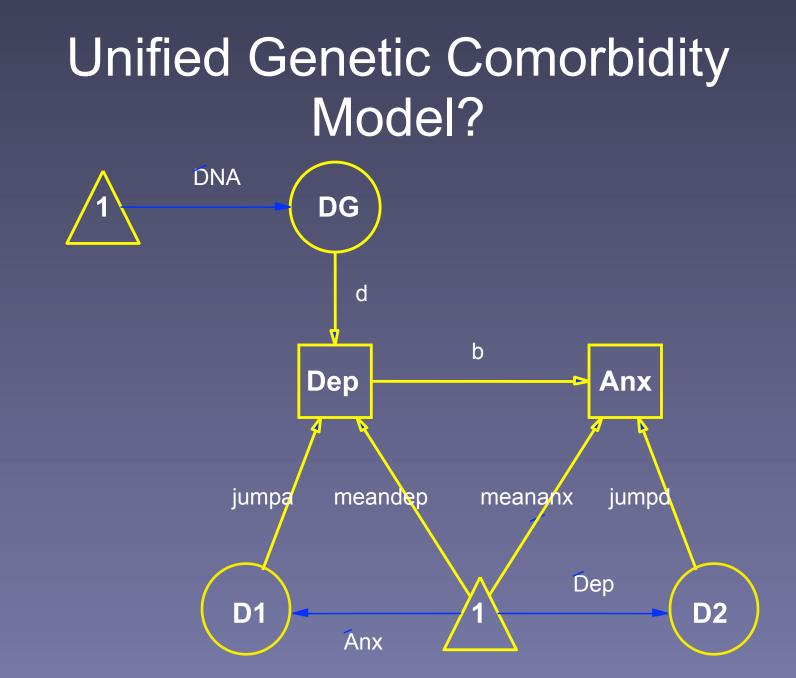
Three Independent Disorders

$P(\overline{A}1, \overline{B}1, \overline{A}2, \overline{B}2) = LL_{A} \cdot LL_{AB} \cdot LL_{B}$	(60)
$P(\overline{A}1, \overline{B}1, \overline{A}2, B2) = LL_A \cdot LL_{AB} \cdot LU_B$	(61)
$P(\overline{A}1, \overline{B}1, A2, \overline{B}2) = LU_{A} \cdot LL_{AB} \cdot LL_{B}$	(62)
$P(\overline{A}1, \overline{B}1, A2, B2) = L_A \cdot LL_{AB} \cdot LL_B + LU_A \cdot LL_{AB} \cdot LU_B$	(63)
$P(\overline{A}1, B1, \overline{A}2, B2) = LL_A \cdot LL_{AB} \cdot UU_B$	(64)
$P(\overline{A}1, B1, A2, \overline{B}2) = LU_A \cdot LL_{AB} \cdot LU_B$	(65)
$P(\overline{A}1, B1, A2, B2) = L_A \cdot LU_{AB} \cdot U_B + LU_A \cdot LL_{AB} \cdot UU_B$	(66)
$P(A1, \overline{B}1, A2, \overline{B}2) = UU_A \cdot LL_{AB} \cdot LL_B$	(67)
$P(A1, \overline{B}1, A2, B2) = L_A \cdot LU_{AB} \cdot L_B + UU_A \cdot LL_{AB} \cdot LU_B$	(68)
$P(A1, B1, A2, B2) = UU_{AB} + UU_A \cdot LL_{AB} \cdot UU_B + 2U_A \cdot LU_{AB} \cdot U_B.$	(69)



Unified Comorbidity Model?





Sources for comorbidity scripts

- <u>http://ibgwww.colorado.edu/cadd/software</u>
- Soo Rhee's website! Excellent!
- Includes covariates e.g., age (Rhee et al submitted)
- Clinical selected samples as well
- Exercise: download and fit the examples and decide on best fit model
- <u>http://www.vcu.edu/mx/examples</u>
- Mike Neale's script website.
- More than a little bit dusty

OpenMx User-defined Functions

Can specify AlgebraObjective

mxAlgebra(MZ.objective + DZ.objective, name="-2sumll"), mxAlgebraObjective("-2sumll"))

- Any mxAlgebra you like!
 Woohoo!
- See, e.g., <u>http://openmx.psyc.virginia.edu/</u> <u>repoview/1/trunk/models/passing/</u> <u>oneLocusLikelihood.R</u>
- One & two locus ABO blood group examples

Comorbidity with covariates

- Soo Rhee's website again
- <u>http://ibgwww.colorado.edu/cadd/software</u>
- These scripts are in classic Mx
- Look out for updates

Possible Extensions

- More than two disorders
- More than one point in time
- More than pairs of twins
- Covariates & GxE
- Models for symptoms (IRT)
- Dynamical systems models
- Generalization to continuous liability

Possible Exercises

- Modify directionofCausation.R to fit:
 - Anxiety (P2) causes depression (P1)
 - Bidirectional causation (tricky, may need bounds)
 - Test hypothesis that comorbidity in ACE bivariate is purely due to rG
- Use tableFitStatistics function to compare results of ACE & other comorbidity models
- Find some other data, rinse & repeat...

Comorbidity Depression & Anxiety Disorders



Alternate form Random Multiformity Random Multiformity of MD Random Multiformity of GAD Extreme Multiformity of MD Extreme Multiformity of GAD Extreme Multiformity of GAD Three Separate Disorders Correlated Liability ACE MD causes GAD GAD causes MI

DSM IIIR MD & Alcohol Abuse