

Comorbidity Models: Analysis of Contingency Tables

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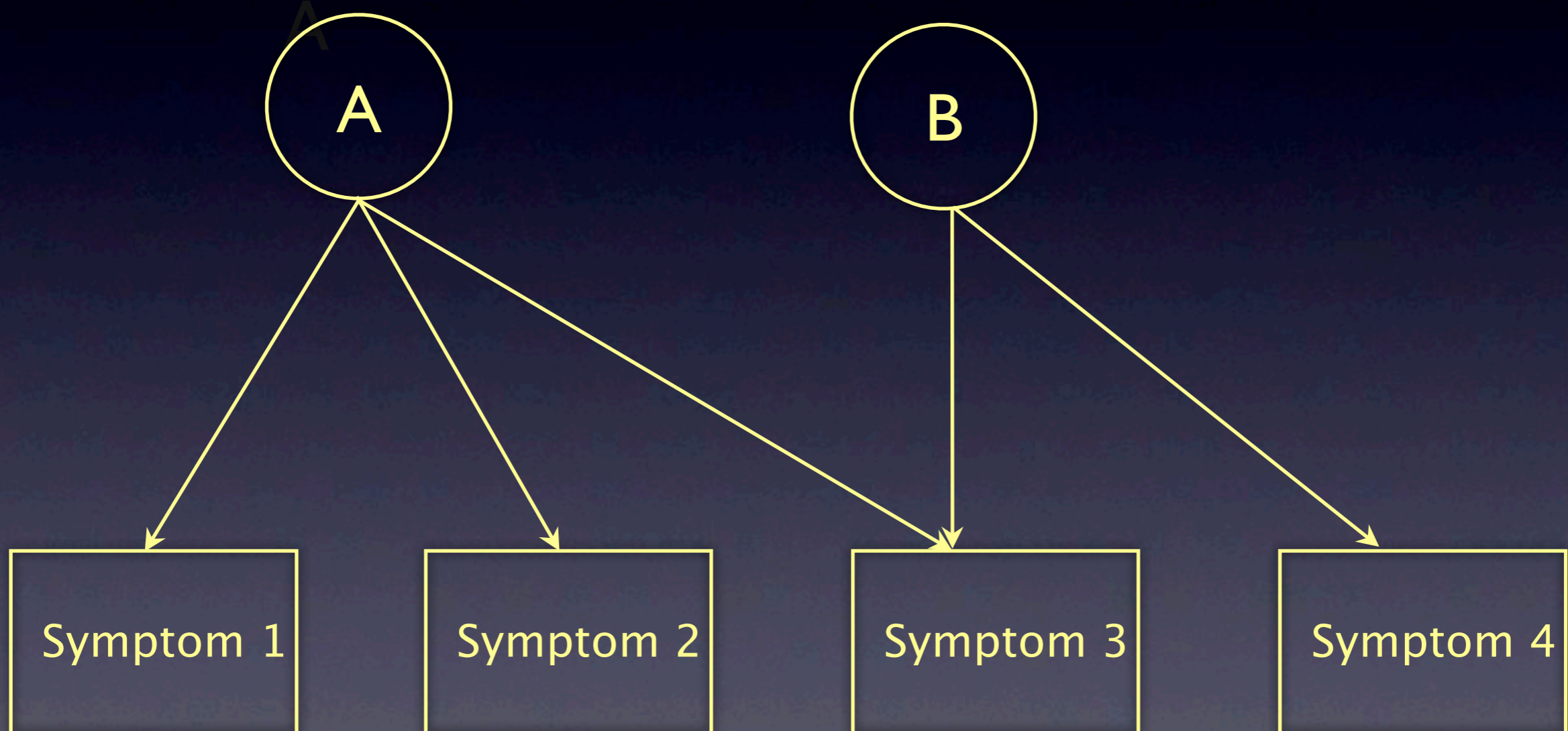


Overview

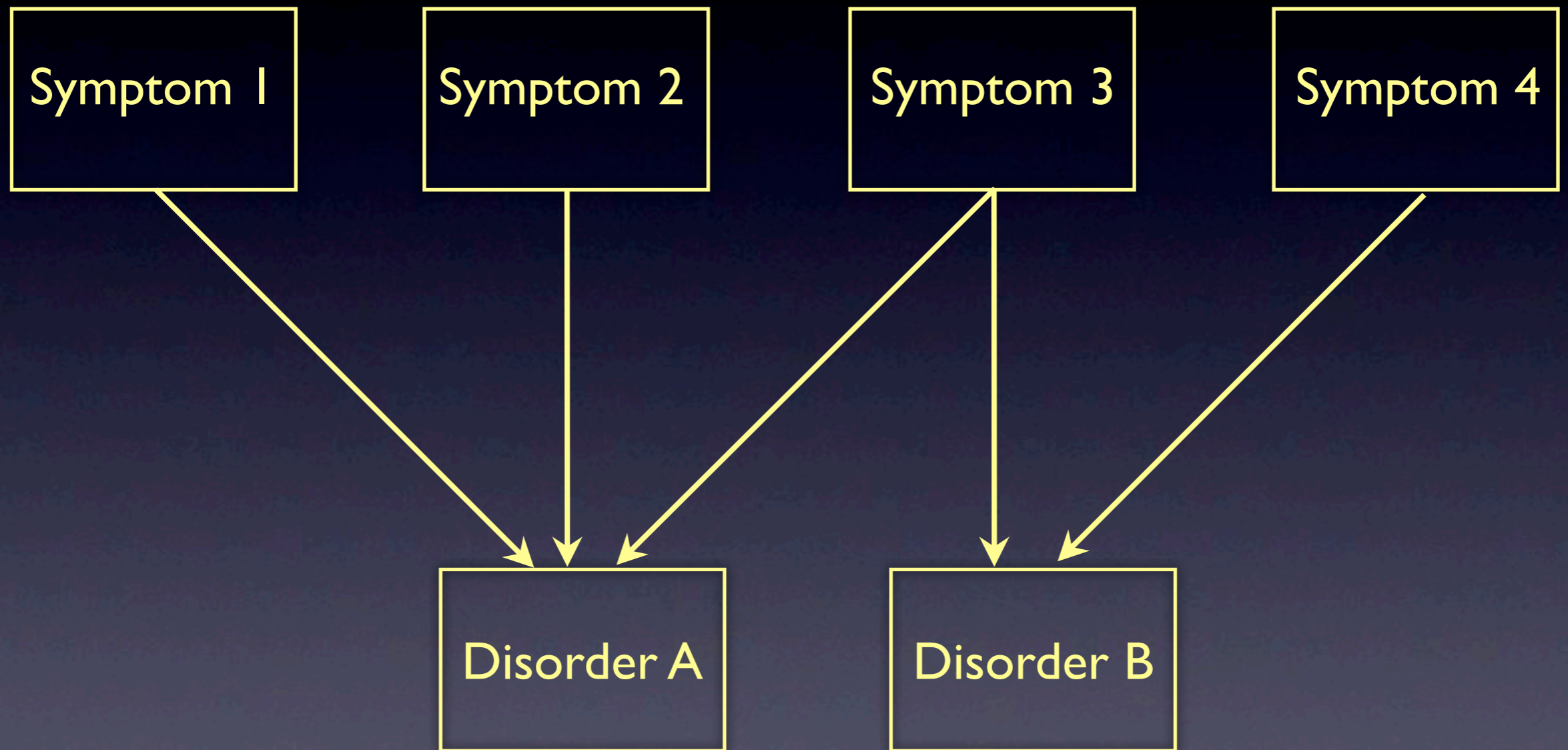
- Substance Use & Disorder Diagnoses:
 - Binary phenotypes
 - Highly comorbid
 - Psychiatric disorders
- ACE model is but one of many
- Two twins, two binary variables
 - 16 outcome combinations
- Fit models by maximum likelihood
 - (alternatives exist)



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



Assessments of disorders A & B share symptoms



Cramer, Waldrop, Van der Maas, Borsboom (2010)

Comorbidity: A network perspective. *Brain Behavior Sciences* 33:137-

Comorbidity due to symptom sharing

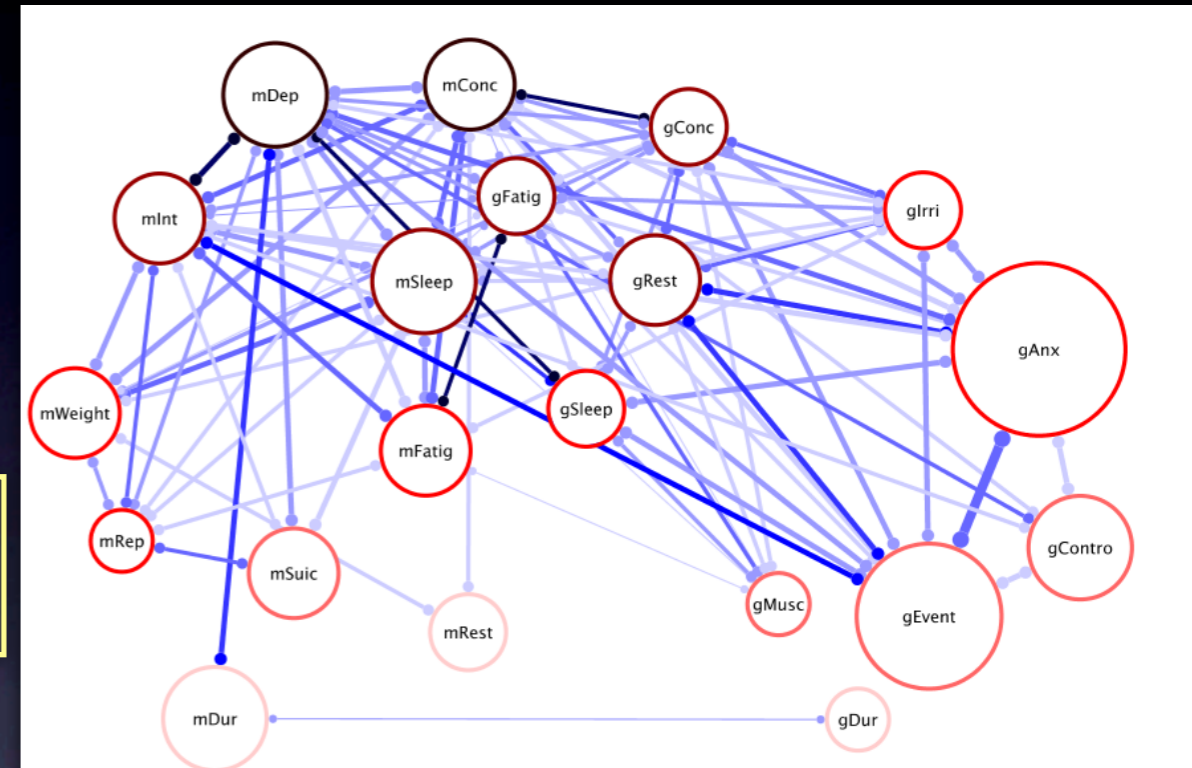
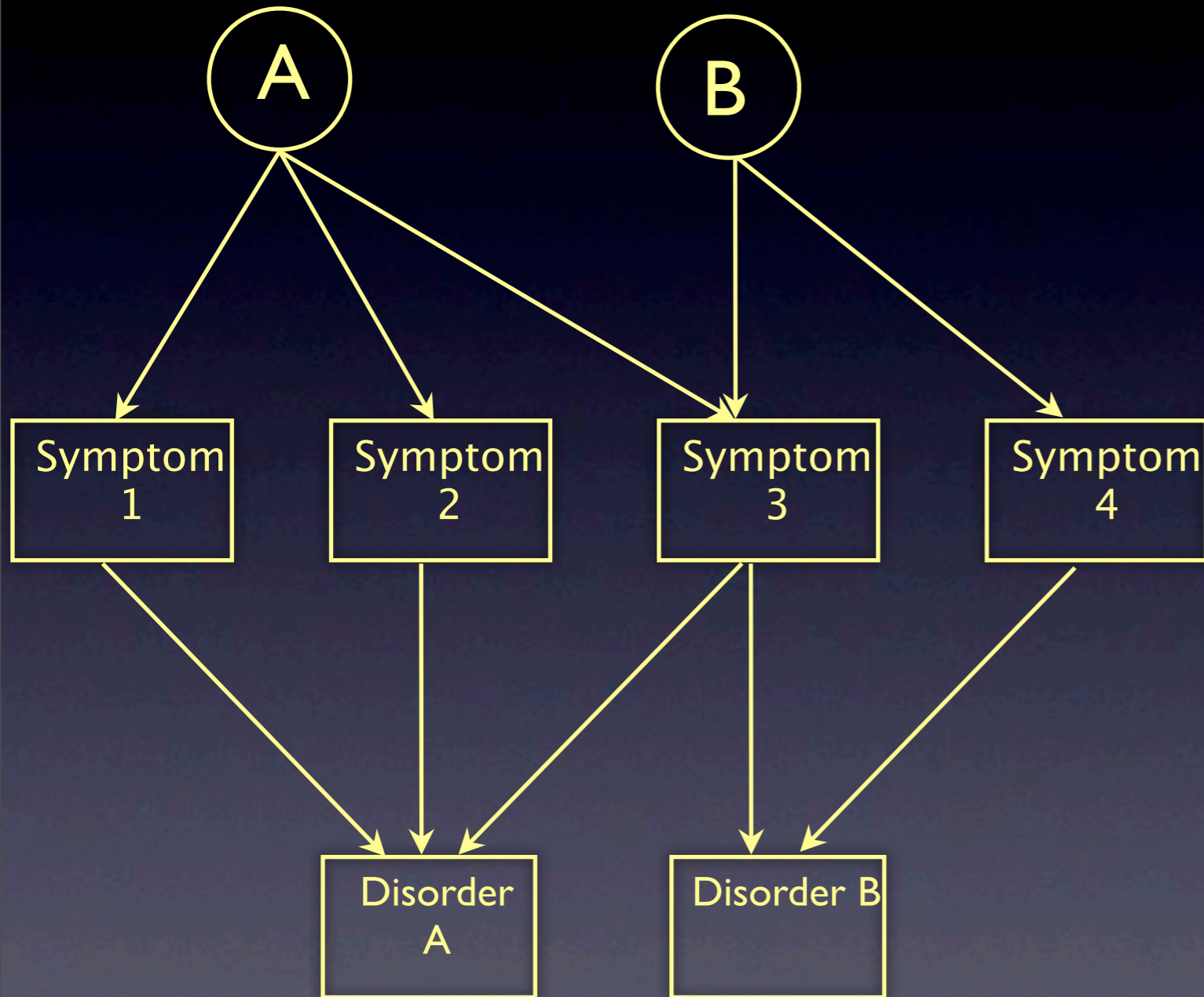


Figure 4. A comorbidity network for MDD and GAD. Larger nodes represent more frequent symptoms; darker circumference, higher centrality; thicker edges, higher frequency of co-occurrence; darker edges, stronger associations. Only edges with a log odds ratio higher than (-) 0.60 are represented. Centrally positioned nodes (*mConc*, *gConc*, *mSleep*, *gSleep*, *mFatig*, *gFatig*, *mRest* and *gRest*) represent overlapping symptoms. Non-overlapping MDD symptoms are displayed on the left of the figure, non-overlapping GAD symptoms on the right.

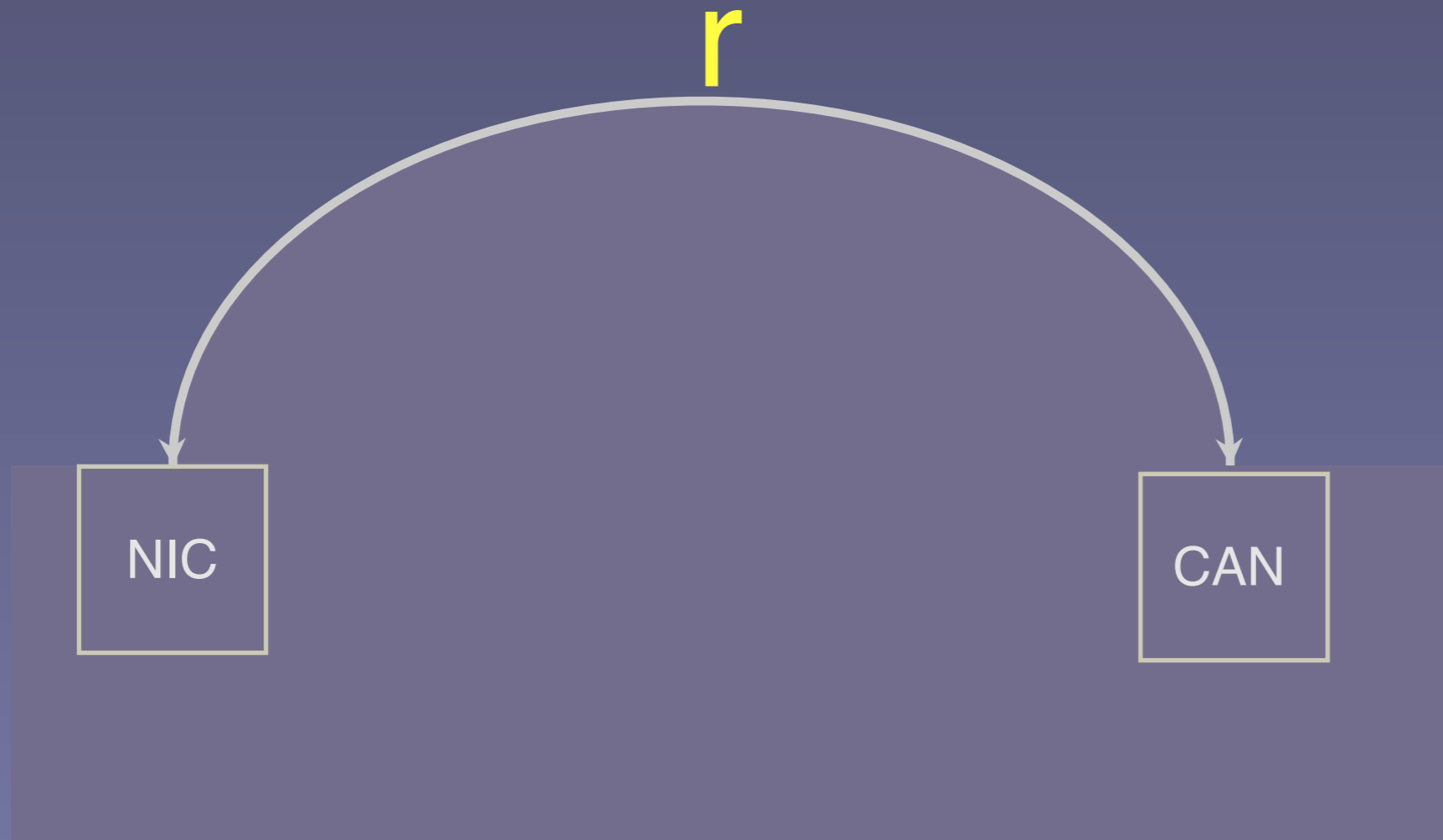
Not today!

Comorbidity

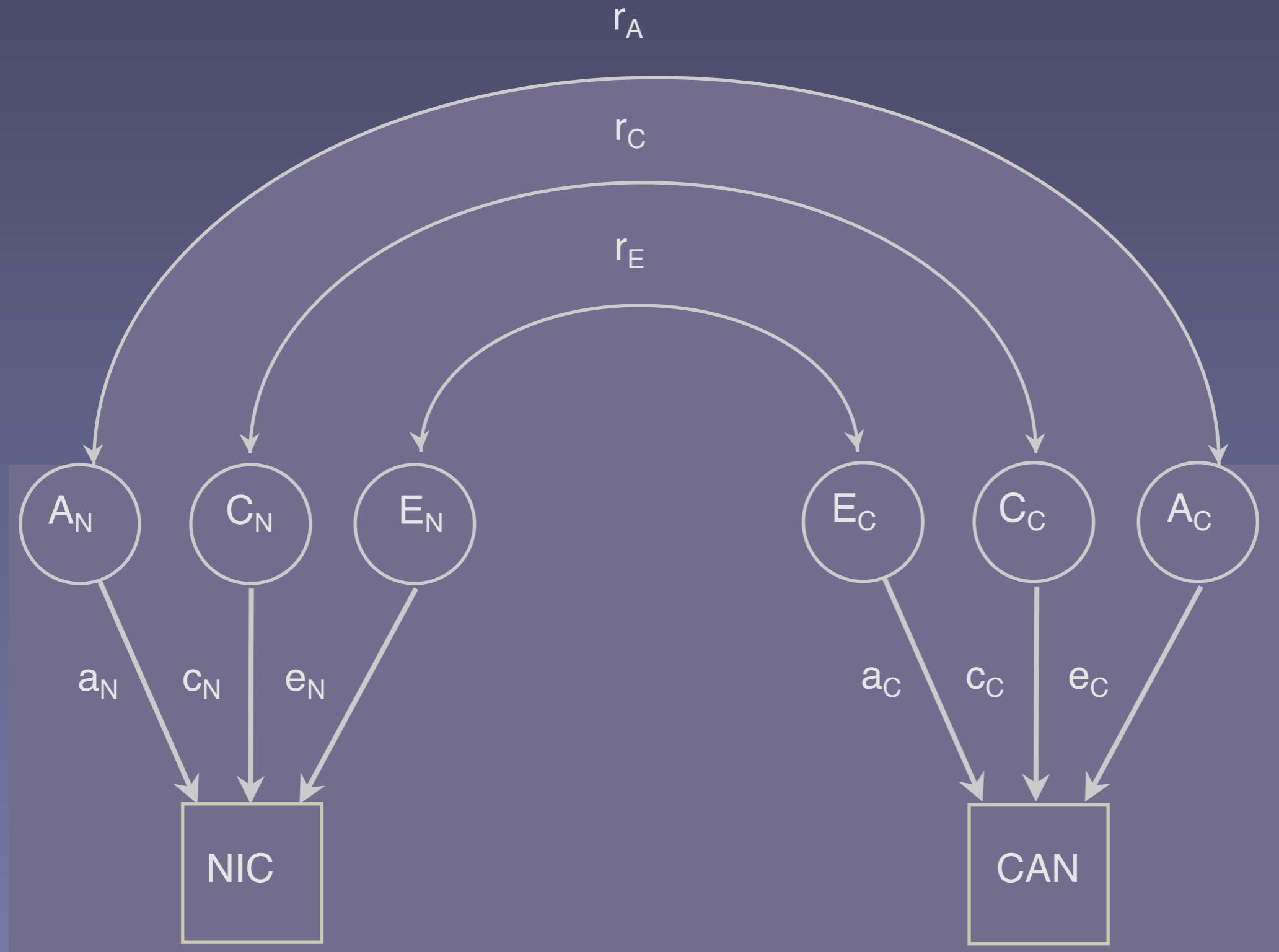
A correlation between (binary) traits

Neale & Kendler (1995) 13 Models

Based on Klein & Riso (1994)

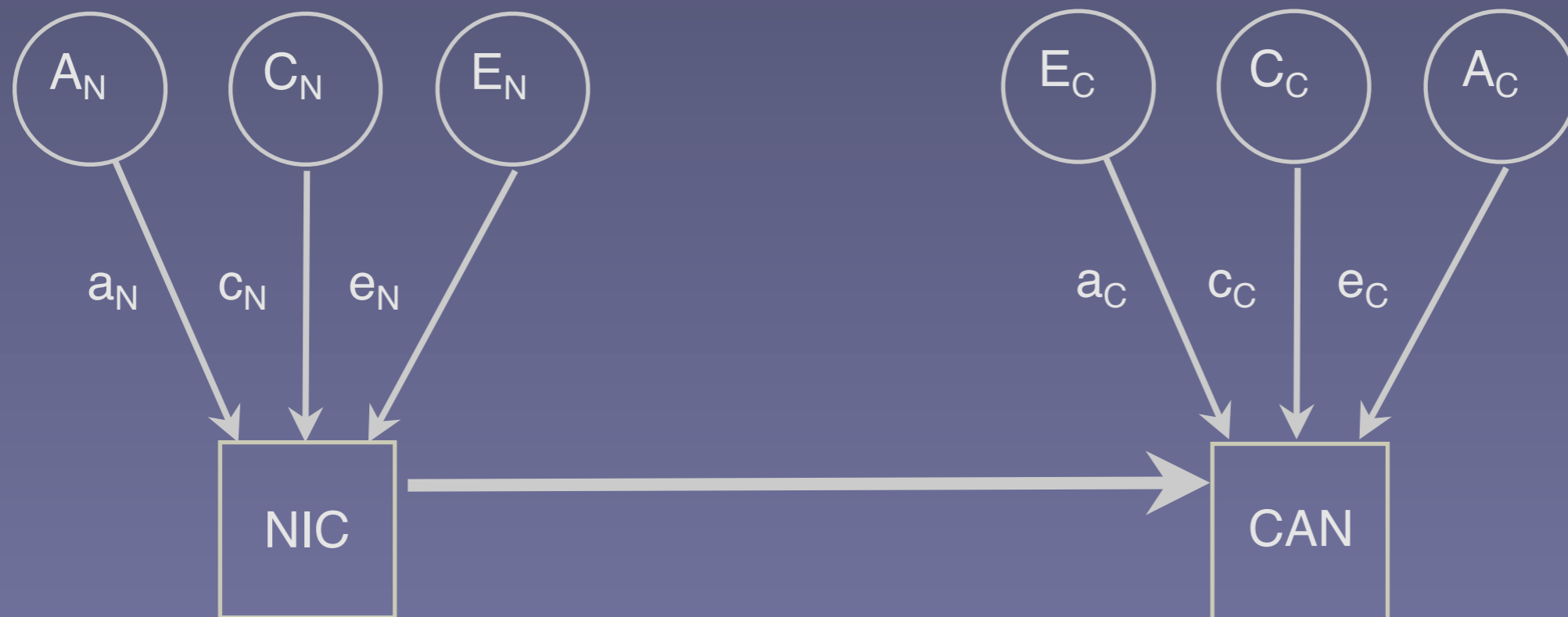


Partitioning Comorbidity



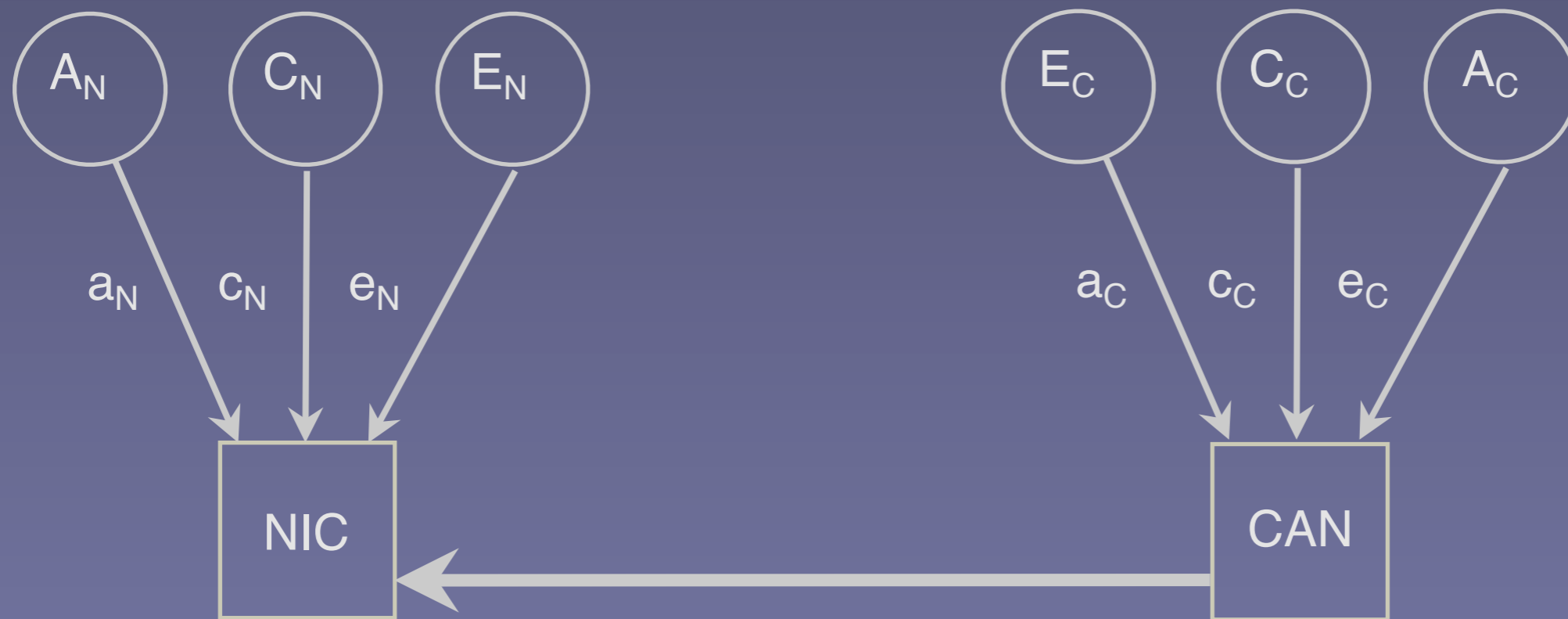
Modeling Comorbidity

Nicotine Use Causes Cannabis Use



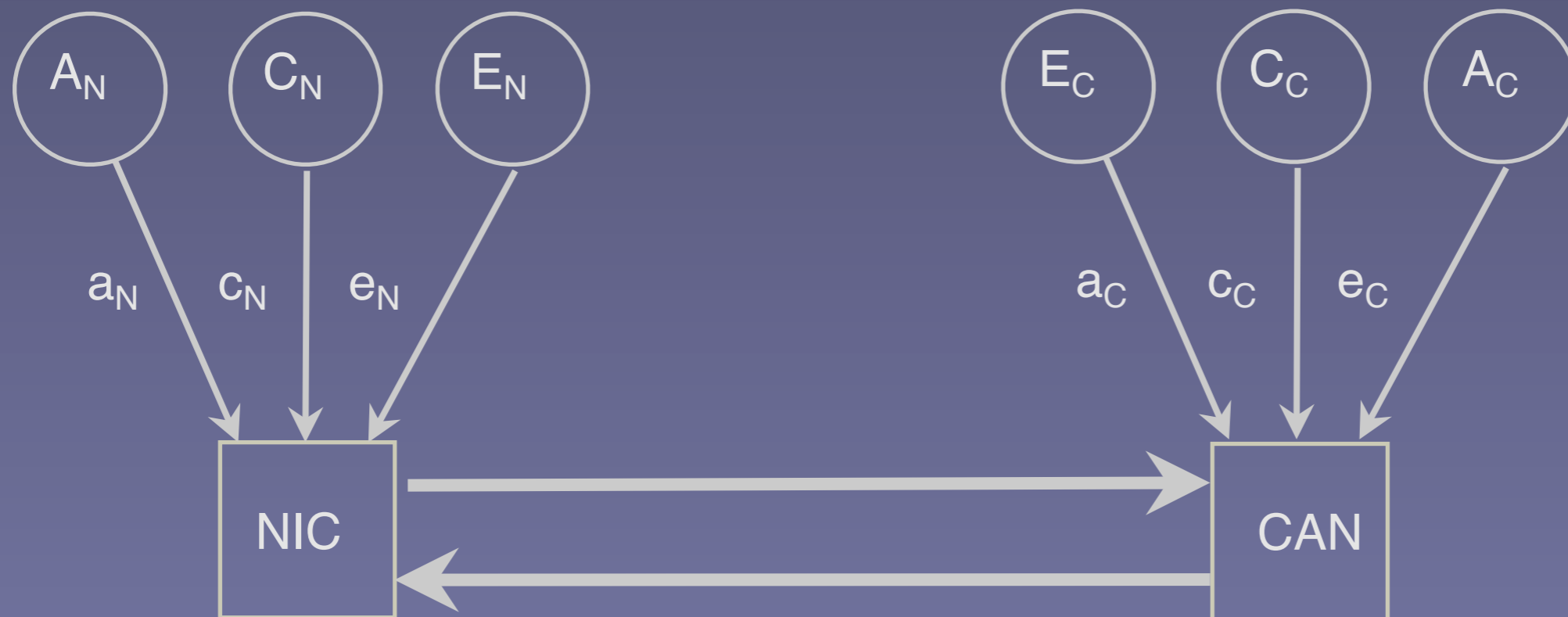
Modeling Comorbidity

Cannabis Use Causes Nicotine Use



Modeling Comorbidity

Reciprocal Causation



Multinomial Likelihood

If data $x_i, i=1 \dots n$ fall into k different classes with probability $p_j, j=1 \dots k$, and n_j is the number falling into class j ,

$$\text{Likelihood} = \prod_{j=1}^k p_j^{n_j}$$

$$\text{Log-likelihood} = \sum_{j=1}^k n_j \log(p_j)$$

MLE of proportion is observed proportion

Directly obtain MLE of $p_j, j=1 \dots k$ as n_j/n

Data Tabulation

		Twin 2		Yes	
		No	Yes	No	Yes
Twin 1	No	----	---+	--+-	--++
	Yes	-+--	-+-+	-+++	-++++
Yes	No	+----	+---+	+--+	+--+
	Yes	++--	++-+	+++-	++++

Symmetric

		Twin 2			
		No	Yes	No	Yes
Twin 1	No	No	Yes	No	Yes
	No	No	----	---+	--+-
No	Yes	-+--	-+-+	-+++	-++++
Yes	No	+---	+--+	+--+	+---+
	Yes	++--	++-+	+++-	++++

10 Flavors: Sum across Diagonal

		Twin 2					
		No	Yes	No	Yes		
Twin 1	No	No	Yes	No	Yes		
	No	No	----	---+	--+-	--++	
Yes	Yes		-+-+	-+++	-++++		---+
Yes	No			+--+	+---		--+-
	Yes				++++		-+-+
							+--+
							+---

Multinomial Likelihood R function

```
mzFreqs <- c(141, 35, 32, 25, 15, 7, 33, 39, 47, 124)
dzFreqs <- c(58, 18, 27, 44, 7, 6, 33, 15, 38, 81)
satLogLike <- function(x) {
  proportions <- x/sum(x)
  logliks <- (log(proportions)*x)
  neg2ll <- -2*sum(logliks)
  return(list(neg2lnL=neg2ll))
}
satlnLmz <- satLogLike(mzFreqs)
satlnLdz <- satLogLike(dzFreqs)
satlnL <- satlnLmz$neg2lnL + satlnLdz$neg2lnL
```

Correlated Liabilities

$$\begin{aligned} & P(A1, B1, A2, B2) \\ &= \iint \iint \iint \phi(R_{A1}, R_{B1}, R_{A2}, R_{B2}) \\ & \quad dR_{B2} dR_{A2} dR_{B1} dR_{A1} \end{aligned} \tag{70}$$

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

Bivariate Threshold Model

Contingency Table with 4 observed cells:

cell a: pairs concordant for unaffected

cell d: pairs concordant for affected

cell b/c: pairs discordant for the disorder

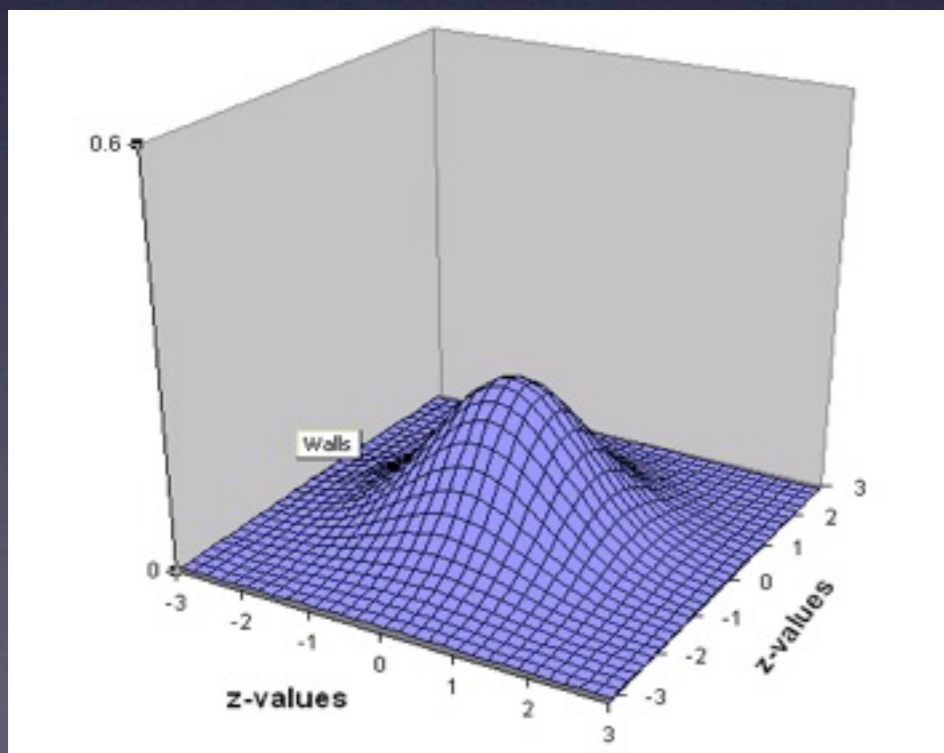
		Twin1	
		0	1
Twin2	0	a	b
	1	c	d

0 = unaffected
1 = affected

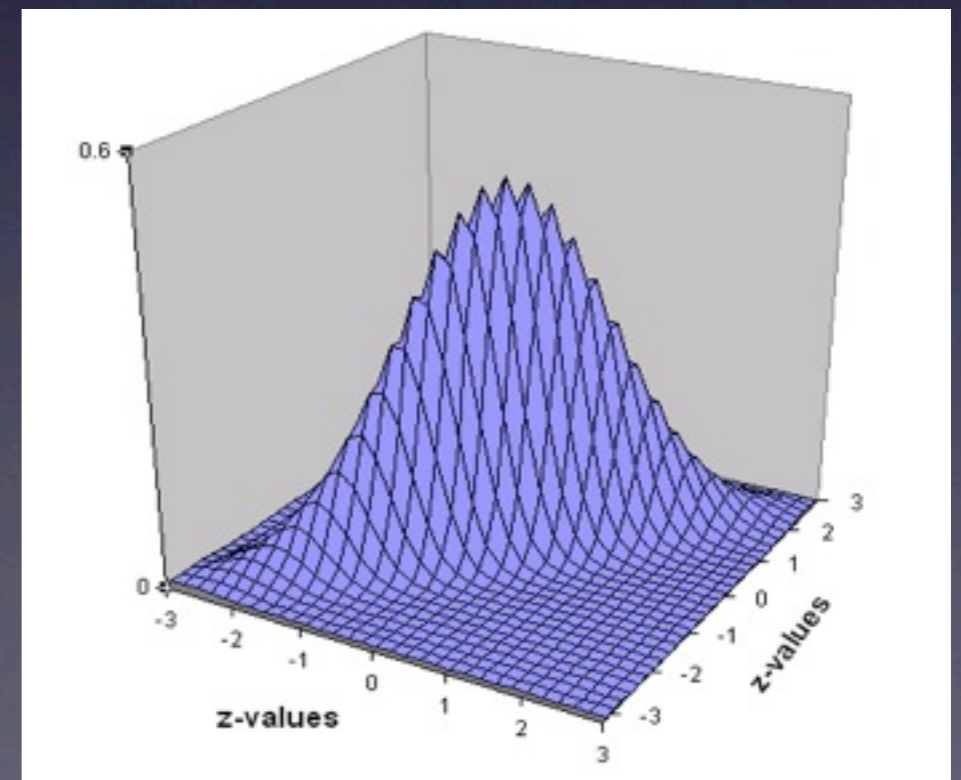
Joint Liability Model for Twin Pairs

- Assumed to follow a **bivariate normal distribution**, where both traits have a mean of 0 and standard deviation of 1, but the **correlation** between them is variable.
- The **shape** of a bivariate normal distribution is determined by the **correlation** between the traits

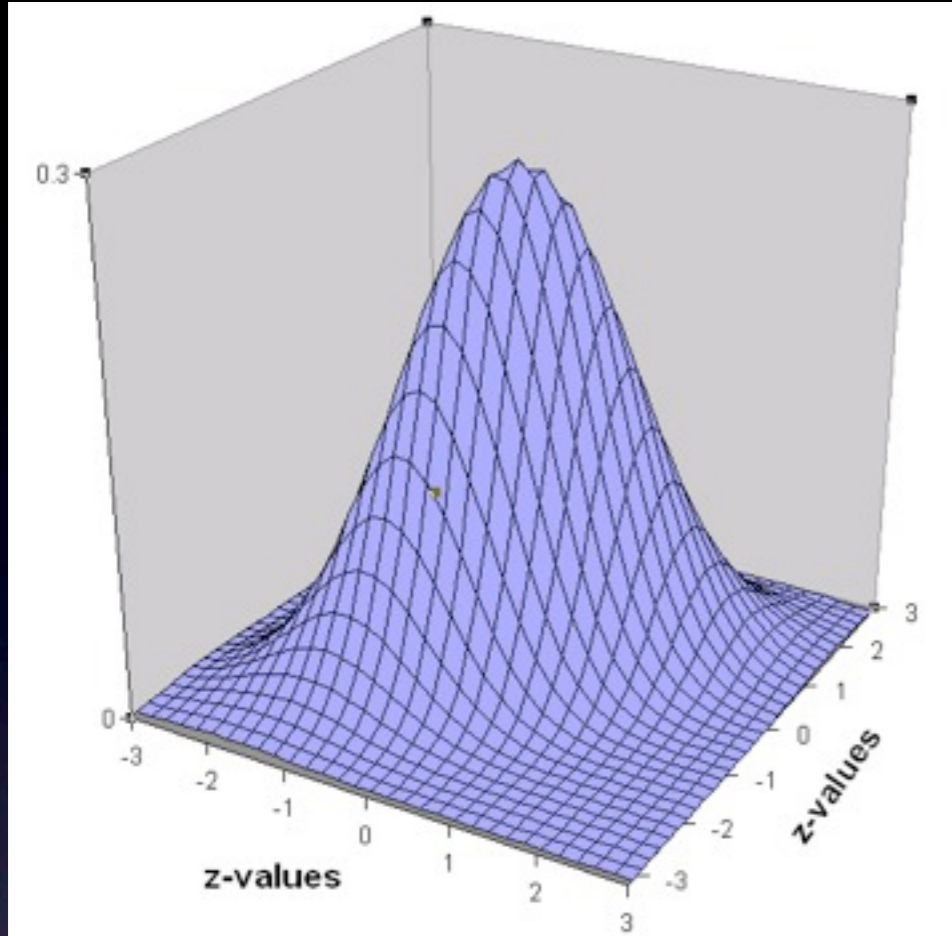
$$r = .00$$



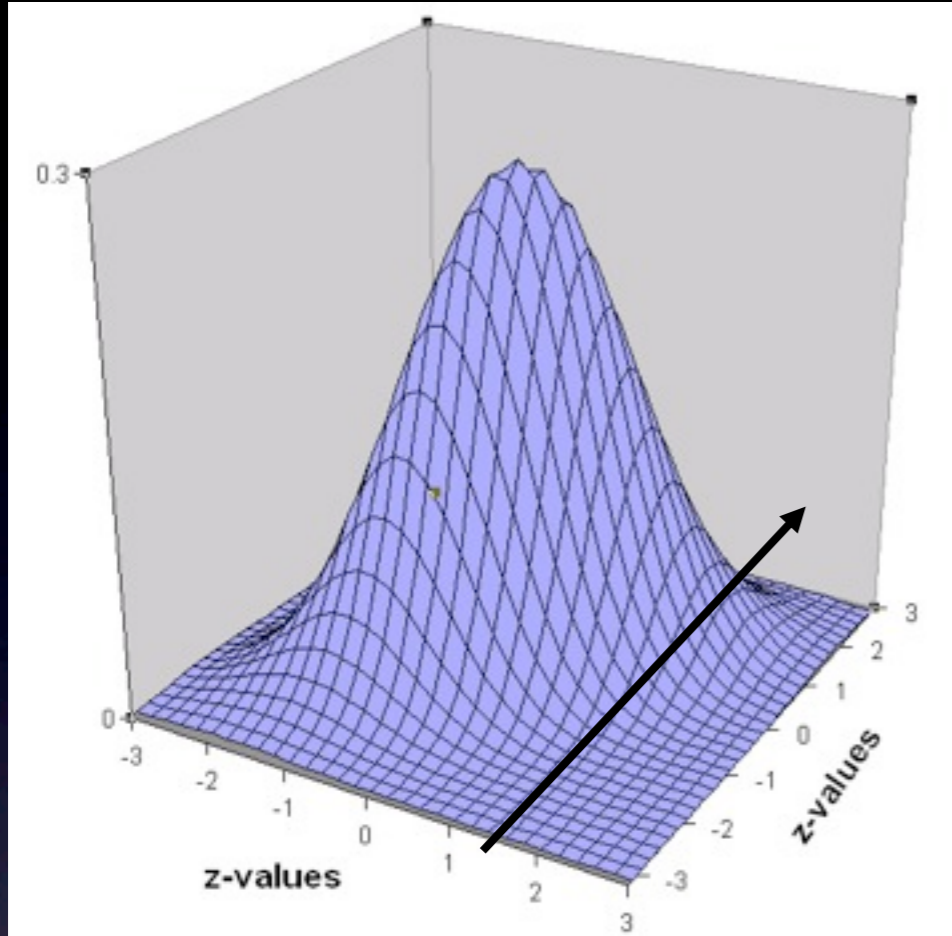
$$r = .90$$



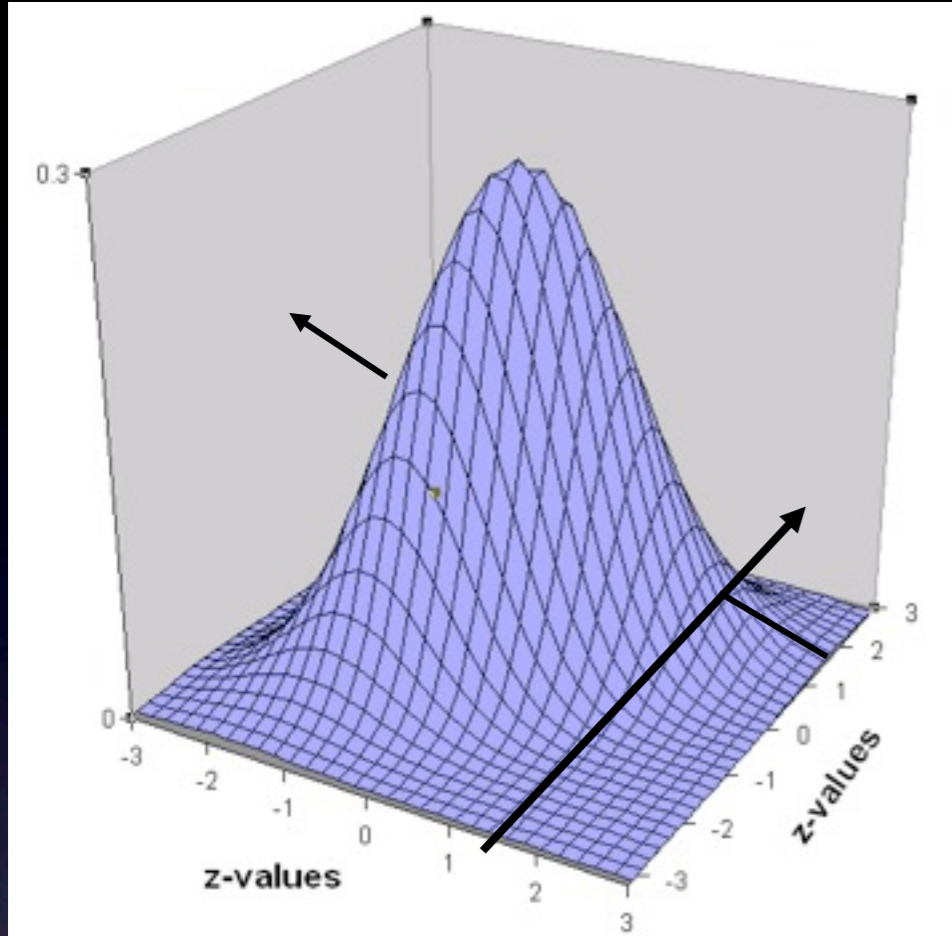
Bivariate Normal ($R=0.6$) partitioned at threshold 1.4 (z-value) on both liabilities



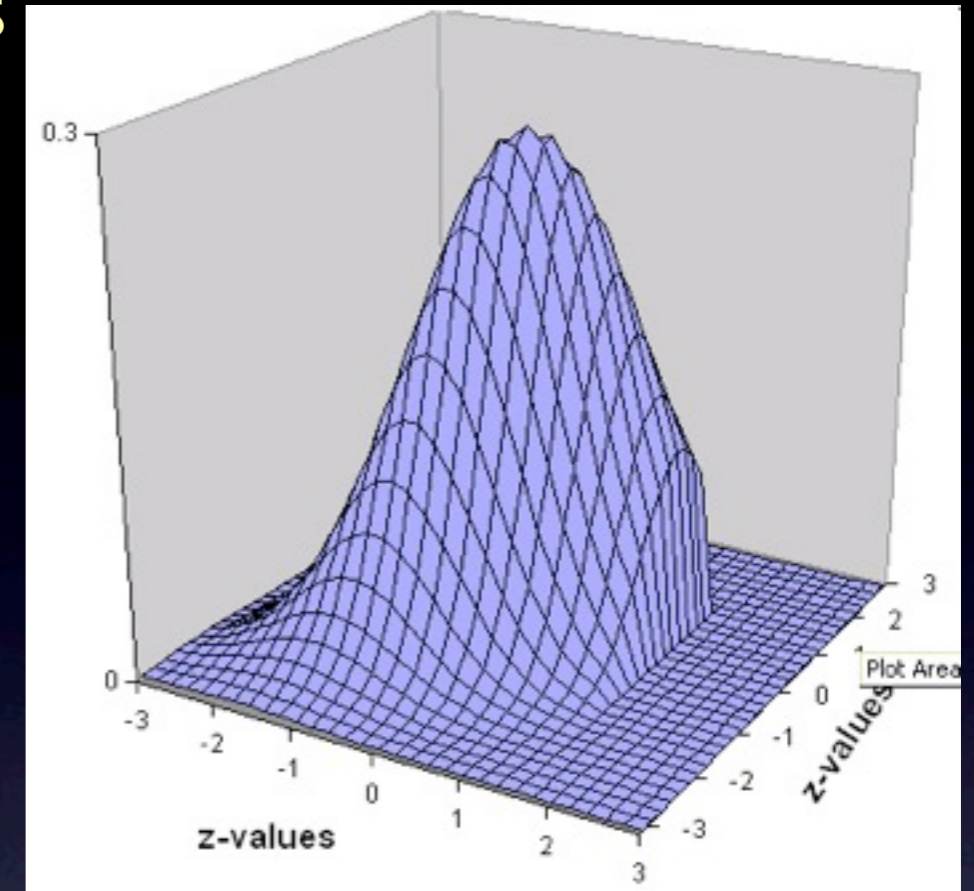
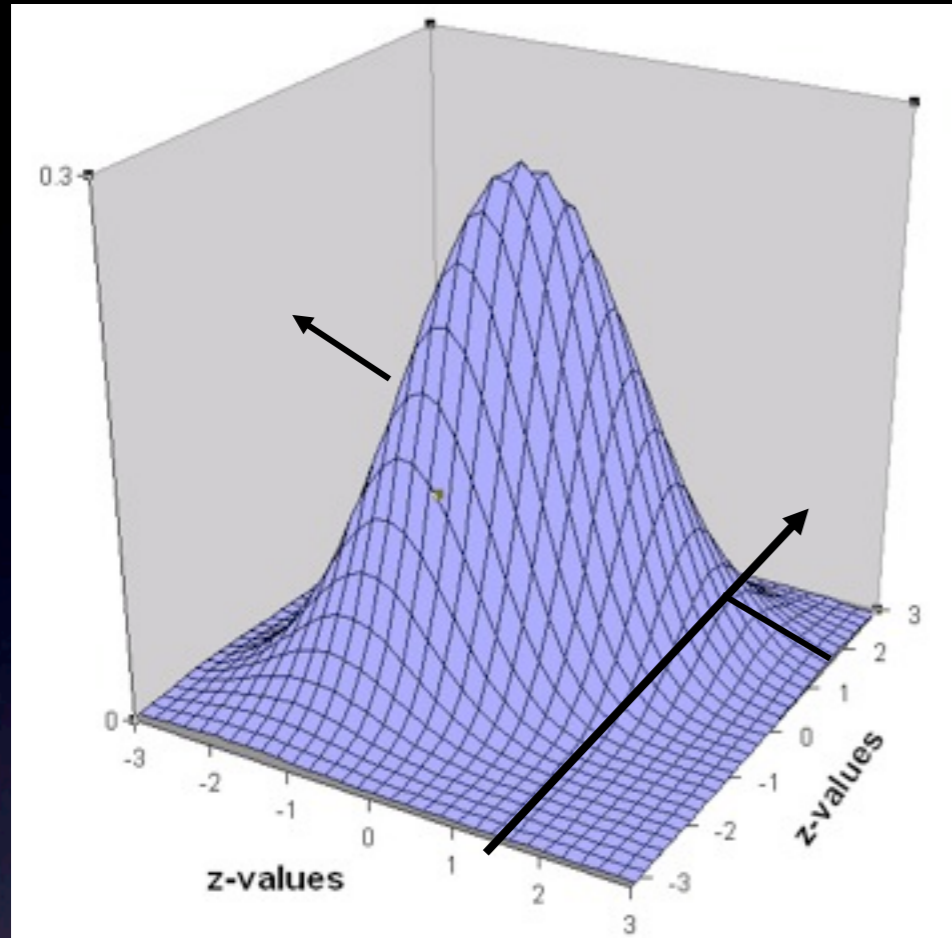
Bivariate Normal ($R=0.6$) partitioned at threshold 1.4 (z-value) on both liabilities



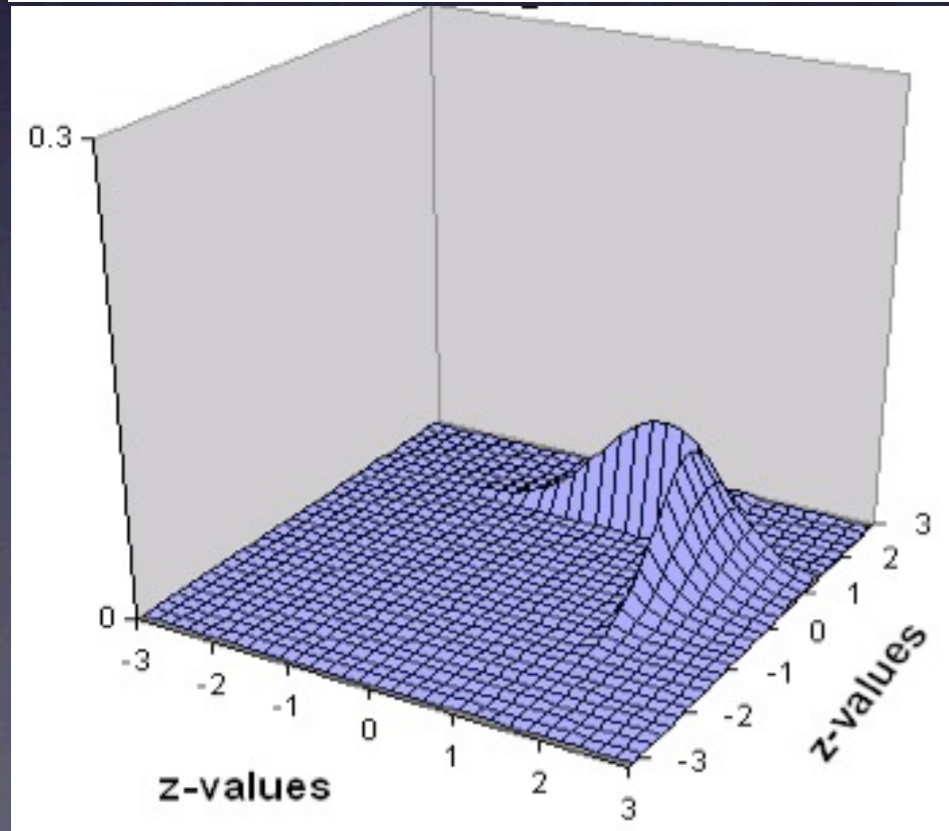
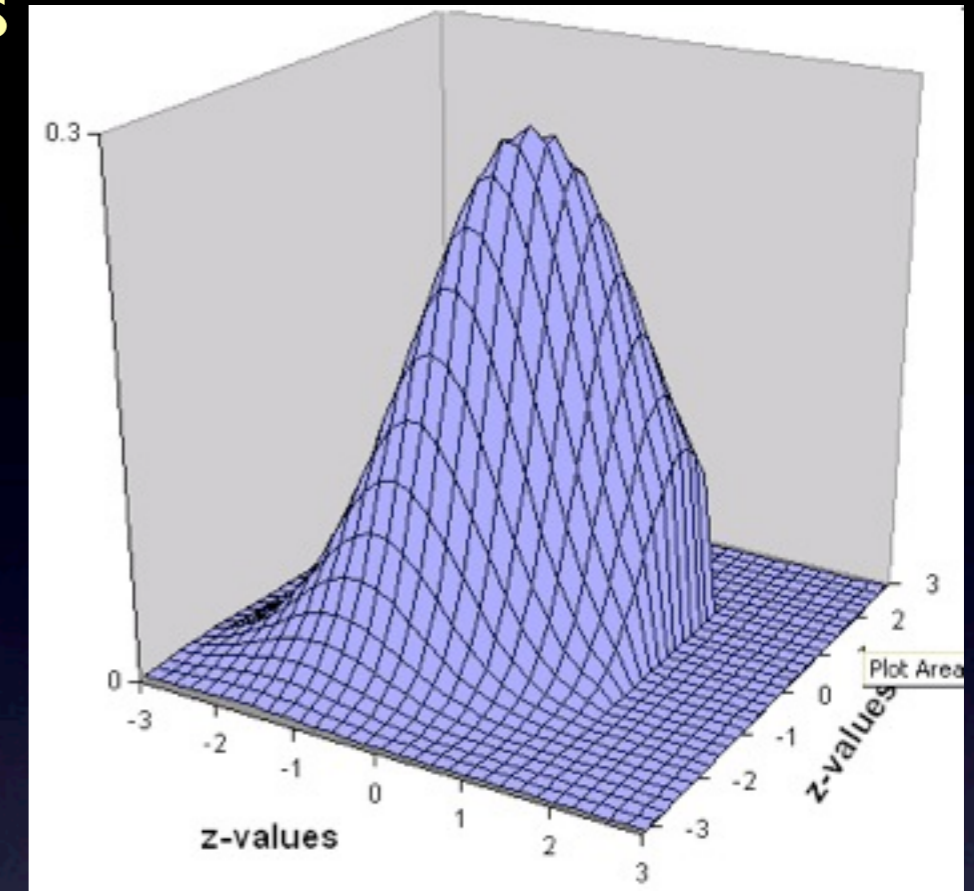
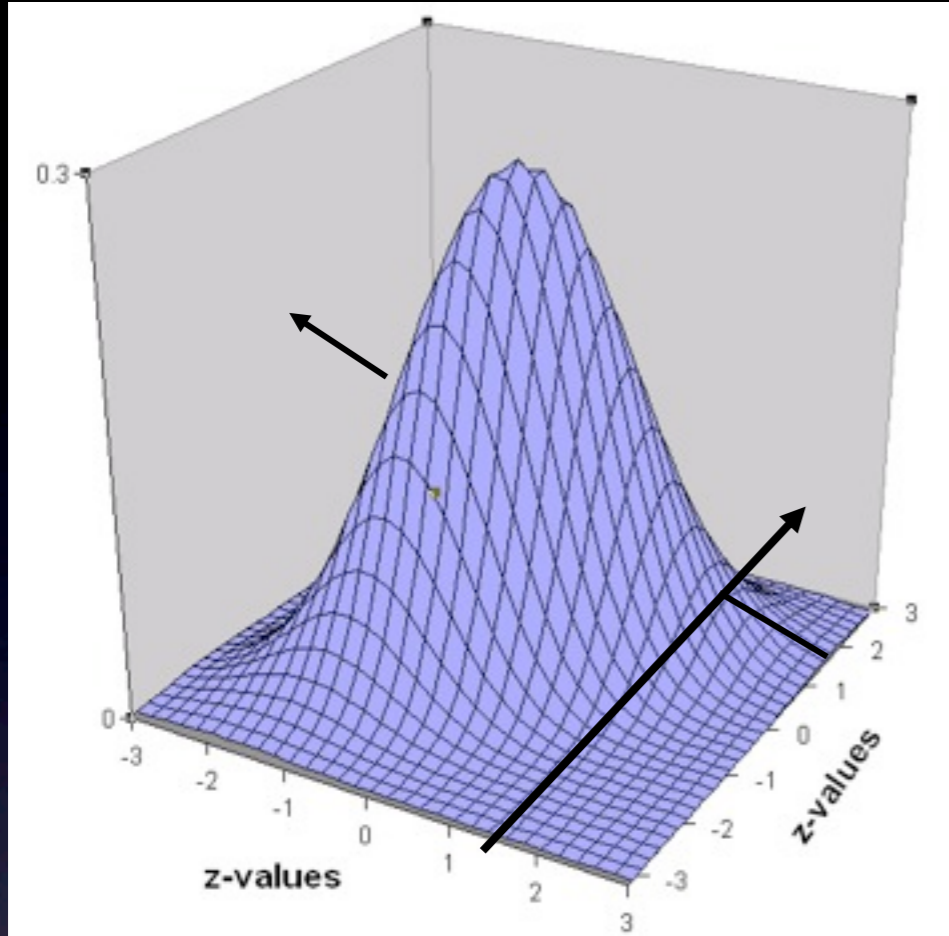
Bivariate Normal ($R=0.6$) partitioned at threshold 1.4 (z-value) on both liabilities



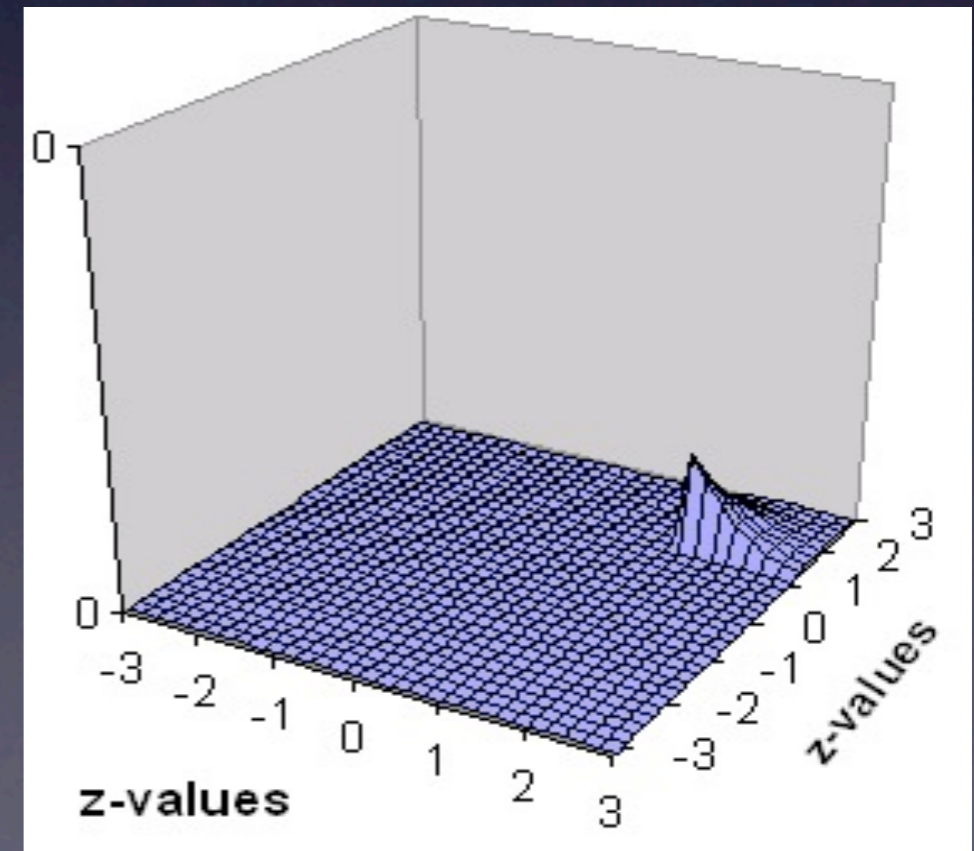
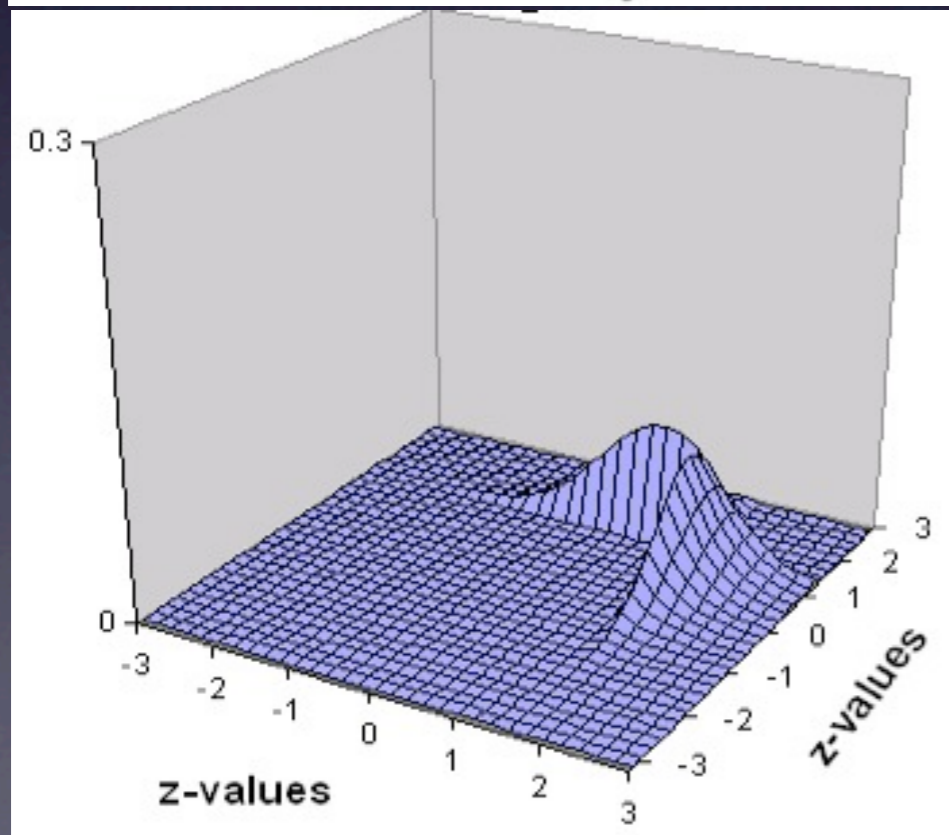
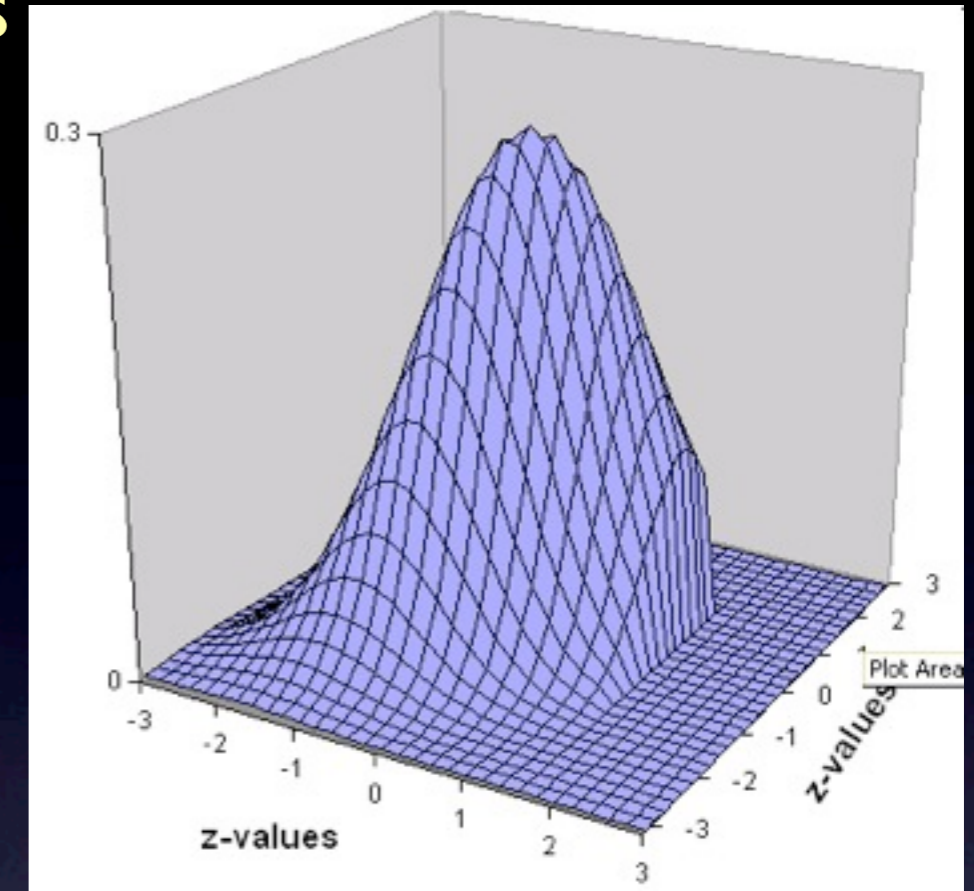
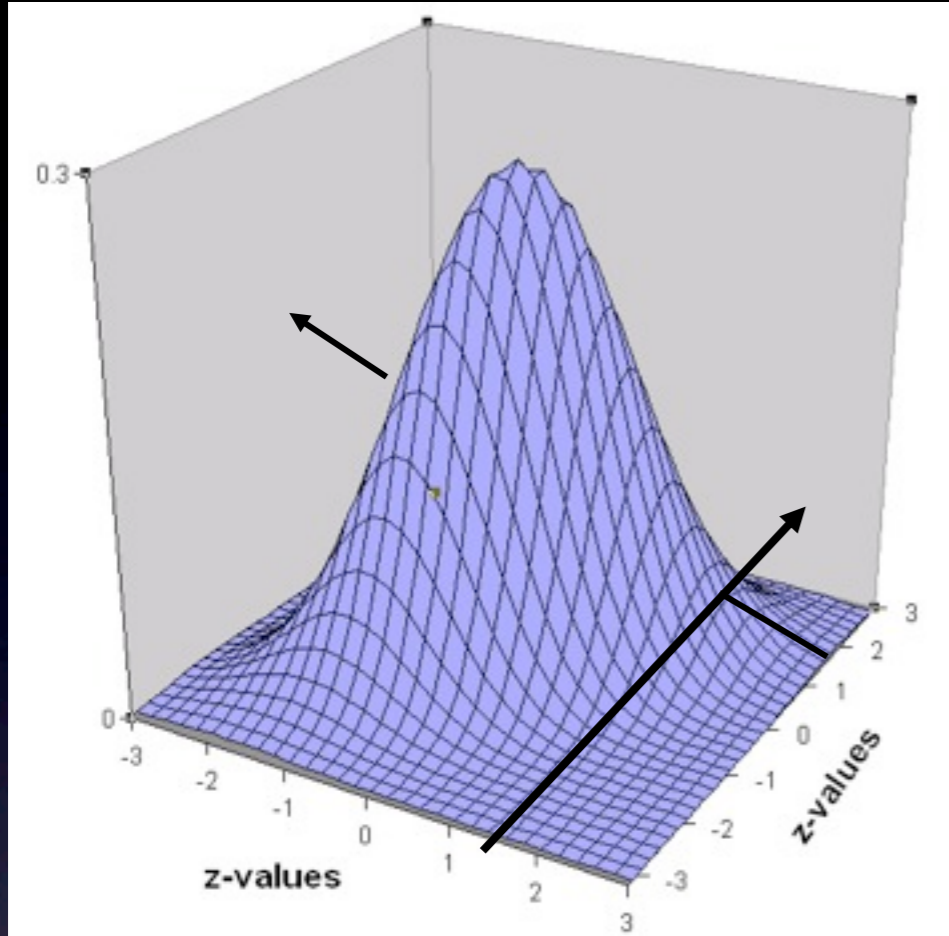
Bivariate Normal ($R=0.6$) partitioned at threshold 1.4 (z-value) on both liabilities



Bivariate Normal ($R=0.6$) partitioned at threshold 1.4 (z-value) on both liabilities

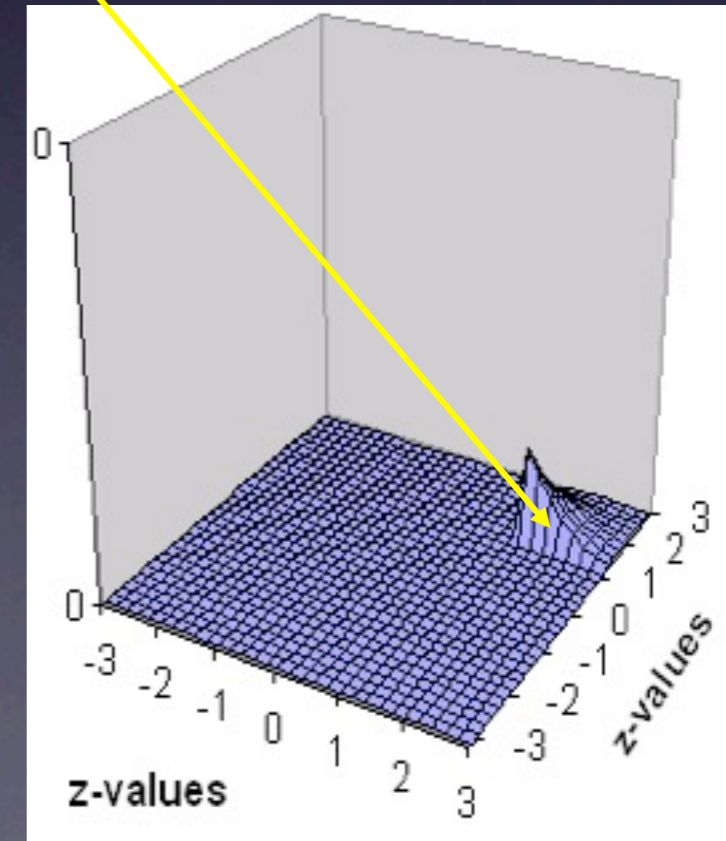
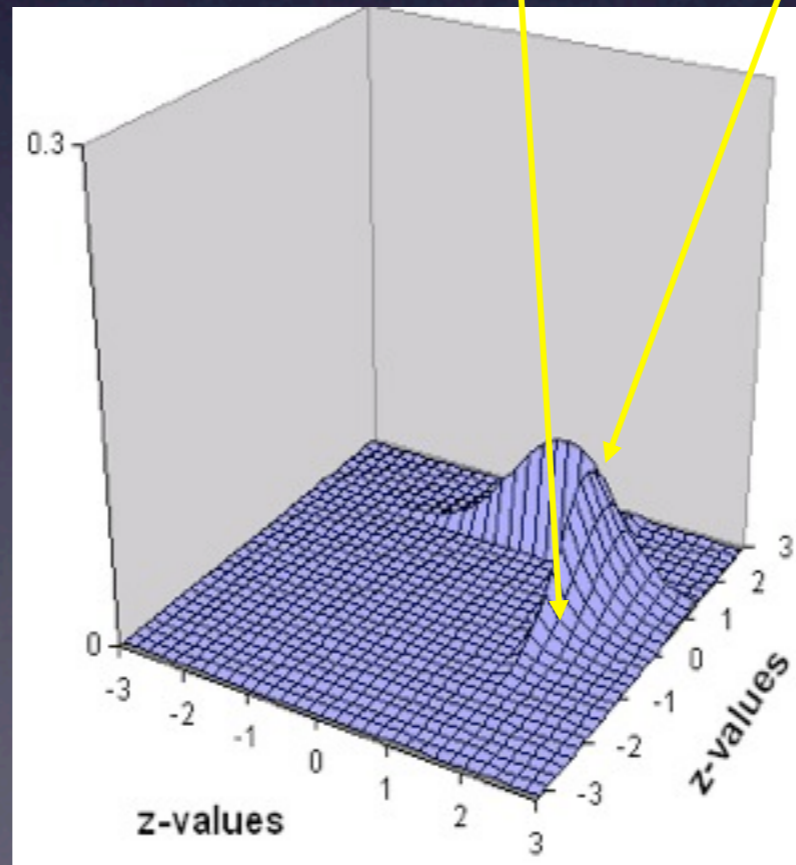
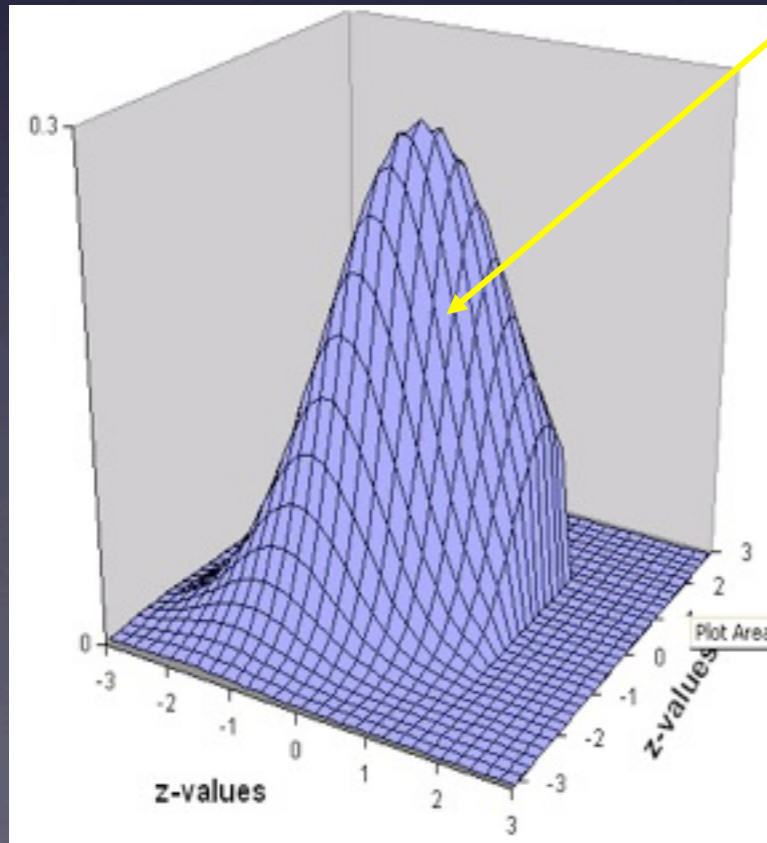


Bivariate Normal ($R=0.6$) partitioned at threshold 1.4 (z-value) on both liabilities



Expected Proportions of the BN, for $R=0.6$, $Th1=1.4, Th2=1.4$

		Liab 2	
Liab 1		0	1
0		.87	.05
1		.05	.03



DOC Model by hand

```
# Make a little labeling function
labFun <- function(name="matrix",nrow=1,ncol=1)
{
  matlab <- matrix(paste(rep(name, each=nrow*ncol), rep(rep(1:nrow),ncol), rep(1:ncol,each=nrow),sep="_"))
  return(matlab)
}

# Matrices a, c, and e to store a, c, and e path coefficients
aMat <- mxMatrix( type="Diag", nrow=nv, ncol=nv, free=TRUE, values=.6, labels=labFun("a",nv,nv), name="a" )
cMat <- mxMatrix( type="Diag", nrow=nv, ncol=nv, free=TRUE, values=.6, labels=labFun("c",nv,nv), name="c" )
eMat <- mxMatrix( type="Diag", nrow=nv, ncol=nv, free=TRUE, values=sqrt(.28), labels=labFun("e",nv,nv), name="e" )
BMat <- mxMatrix( type="Full", nrow=nv, ncol=nv, free=c(F,T,F,F), labels=labFun("B",nv,nv), name="B" )

# Algebras A, C, and E compute variance components
AAlg <- mxAlgebra( expression=a %*% t(a), name="A" )
CAlg <- mxAlgebra( expression=c %*% t(c), name="C" )
EAlg <- mxAlgebra( expression=e %*% t(e), name="E" )

# Algebra to compute total variances and standard deviations (diagonal only)
VALg <- mxAlgebra( expression=diag2vec(A+C+E), name="V" )
UMat <- mxMatrix( type="Unit", nrow=nv, ncol=1, name="U" )
IMat <- mxMatrix( type="Iden", nrow=nv, ncol=nv, name="I" )
sdAlg <- mxAlgebra( expression=solve(vec2diag(sqrt(V))), name="sd" )
thresholdMat <- mxMatrix( type="Full", nrow=1, ncol=nv, free=TRUE, values=0,
  labels=c("thrV1","thrV2"), lbound=-3, ubound=3, name="threshold" )
infMat <- mxMatrix( type="Full", nrow=1, ncol=nv*2, free=F, values=Inf,name="infinities" )
neginfMat <- mxMatrix( type="Full", nrow=1, ncol=nv*2, free=F, values=-Inf,name="neginfinities" )
thresholdsAlg <- mxAlgebra( expression=rbind(neginfinities,cbind(threshold,threshold),infinities),
  name="thresholds" )
Var1Constraint <- mxConstraint( V==U, name="Var1" )
```

DOC Model by hand

```
# Algebra for Means
MMat      <- mxMatrix( type="Zero", nrow=1, ncol=2*nv, name="M" )
#expMeanAlg <- mxAlgebra( expression= cbind(M,M), name="expMean" )

# Algebra for expected variance/covariance matrix in MZ
expCovMZAlg <- mxAlgebra( expression= (I%x%solve(I-B)) %&% rbind ( cbind(A+C+E , A+C),
                                                                    cbind(A+C , A+C+E)), name="expCovMZ" )

# Algebra for expected variance/covariance matrix in DZ
expCovDZAlg <- mxAlgebra( expression= (I%x%solve(I-B)) %&% rbind ( cbind(A+C+E , 0.5%x%A+C),
                                                                    cbind(0.5%x%A+C , A+C+E)), name="expCovDZ")

# Integrals & expected frequencies, MZ
AllintMZAlg      <- mxAlgebra(omxAllInt(expCovMZ, M, thresholds), name="AllintMZ")
MAllintMZAlg     <- mxAlgebra(cbind(AllintMZ[1:4,],AllintMZ[5:8,],AllintMZ[9:12,],AllintMZ[13:16,]),name="MAllintMZ")
MZExpectedFrequenciesAlg <- mxAlgebra(vech(MAllintMZ+t(MAllintMZ)-vec2diag(diag2vec(MAllintMZ))),name="MZExpectedFrequencies")

# Integrals & expected frequencies, DZ
AllintDZAlg      <- mxAlgebra(omxAllInt(expCovDZ, M, thresholds), name="AllintDZ")
MAllintDZAlg     <- mxAlgebra(cbind(AllintDZ[1:4,],AllintDZ[5:8,],AllintDZ[9:12,],AllintDZ[13:16,]),name="MAllintDZ")
DZExpectedFrequenciesAlg <- mxAlgebra(vech(MAllintDZ+t(MAllintDZ)-vec2diag(diag2vec(MAllintDZ))),name="DZExpectedFrequencies")

# Data
MZObservedFrequenciesMat <- mxMatrix(type="Full", nrow=10, ncol=1, free=FALSE, values=mzFreqs,
                                       name="MZObservedFrequencies")
DZObservedFrequenciesMat <- mxMatrix(type="Full", nrow=10, ncol=1, free=FALSE, values=dzFreqs,
                                       name="DZObservedFrequencies")
```

DOC Model by hand

```
# Build some lists for convenience
commonStuff <- list(aMat, cMat, eMat, BMat, MMat, UMat, IMat, thresholdMat, infMat, neginfMat,
                   AAlg, CAlg, EAlg, VAlg, sdAlg, thresholdsAlg, Var1Constraint)
MZstuff <- list(AllintMZAlg, MAllintMZAlg, expCovMZAlg, MZExpectedFrequenciesAlg, MZObservedFrequenciesMat)
DZstuff <- list(AllintDZAlg, MAllintDZAlg, expCovDZAlg, DZExpectedFrequenciesAlg, DZObservedFrequenciesMat)

# MZ AlgebraObjective and Model
MZalgobjAlg <- mxAlgebra( -2 * sum(MZObservedFrequencies * log(MZExpectedFrequencies)),name="MZalgobj")
MZMod <- mxModel("MZ", commonStuff, MZstuff, MZalgobjAlg, mxAlgebraObjective("MZalgobj"))

# DZ Model
DZalgobjAlg <- mxAlgebra( -2 * sum(DZObservedFrequencies * log(DZExpectedFrequencies)),name="DZalgobj")
DZMod <- mxModel("DZ", commonStuff, DZstuff, DZalgobjAlg, mxAlgebraObjective("DZalgobj"))

# Combined Objective function
neg2sumllAlg <- mxAlgebra( MZ.objective + DZ.objective, name="neg2sumll" )
neg2sumllObj <- mxAlgebraObjective("neg2sumll")

# Combined model of the two groups
DOCModel <- mxModel("DOC", MZMod, DZMod, neg2sumllAlg, neg2sumllObj)

#
# Fit Direction of Causation Model with Cell Frequencies Input
# -----

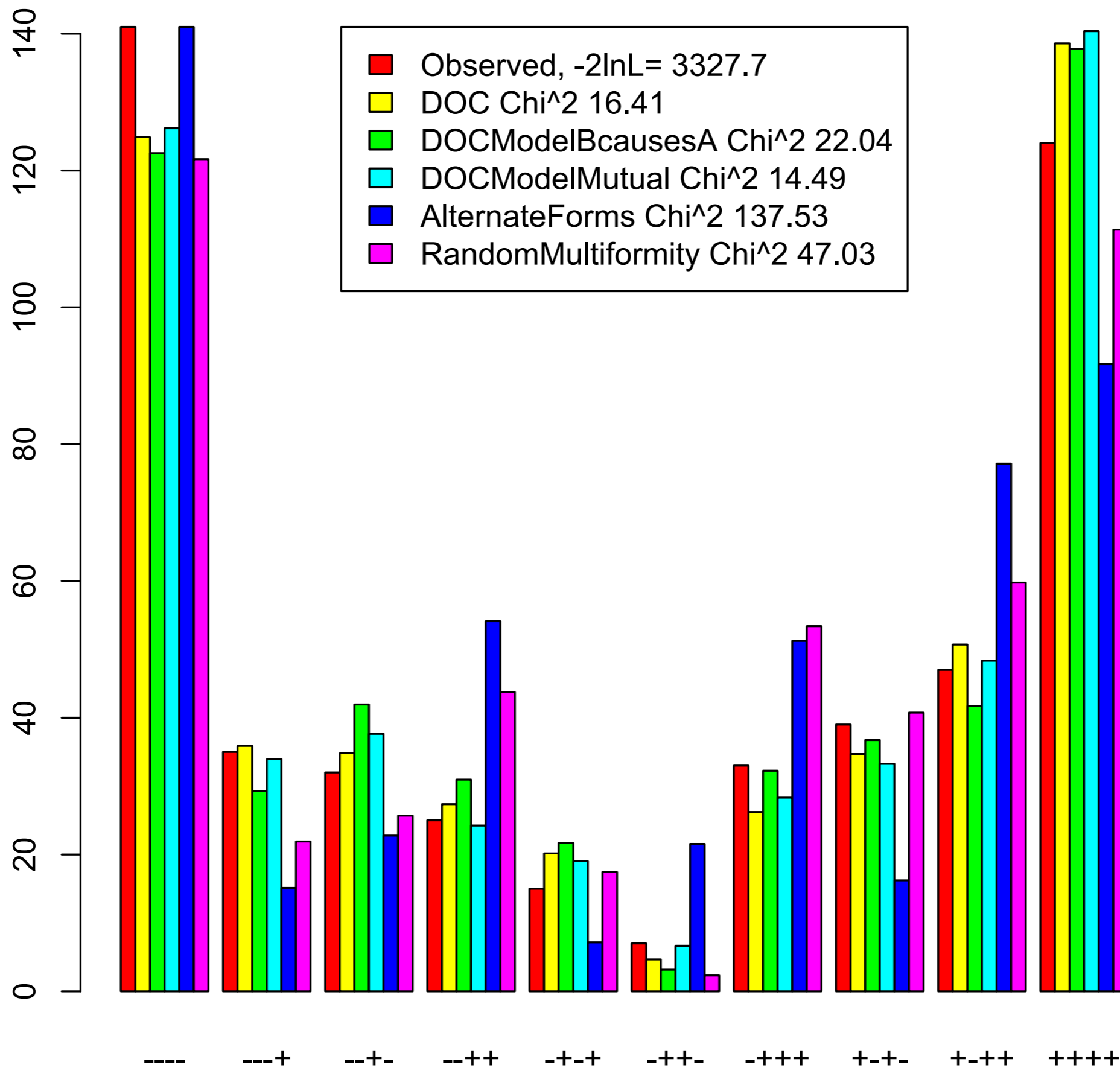
summary(DOCModelFit <- mxRun(DOCModel), numStats=20, SaturatedLikelihood=satlnL)
```

Graphing Results

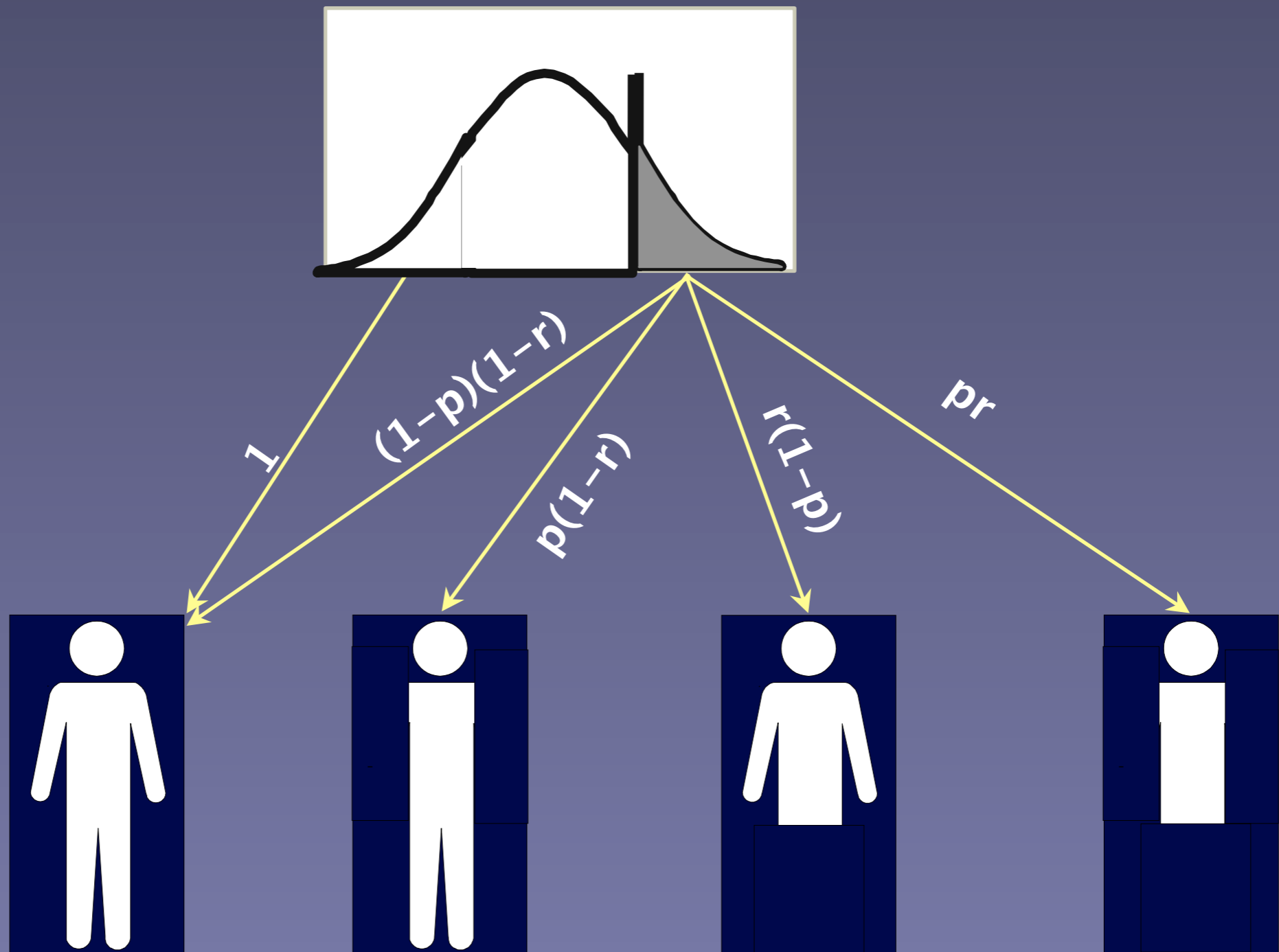
```
satLogLike <- function(x) {
  proportions <- x/sum(x)
  logliks <- (log(proportions)*x)
  neg2ll <- -2*sum(logliks)
  return(list(neg2lnL=neg2ll))
}
# models is a list of models to be graphed, MZObserved & DZObserved are data vectors, MZ is whether to print MZ or DZ
comorbidBarplot <- function (models, MZObserved, DZObserved, title="Comorbidity Model Fits", MZ=TRUE) {
# Compute Saturated -2lnL
satlnLmz <- satLogLike(mzFreqs)
satlnLdz <- satLogLike(dzFreqs)
satlnL <- satlnLmz$neg2lnL + satlnLdz$neg2lnL
# Set up list of models to be plotted
nModels <- length(models)
nameList <- vector(mode="list", nModels+1)
nameList[1] <- paste("Observed, -2lnL=", round(satlnL,2))
counts <- matrix(0, nrow=nModels+1, ncol=length(MZObserved))
colnames(counts) <- c("----", "----+", "--+-", "--++", "-+++", "-+-+", "-+++", "+-+-", "+-++", "++++")
if (MZ) {counts[1,] <- MZObserved} else {counts[1,] <- DZObserved}
for (i in 1:nModels)
{
  tempModel <- models[[i]]
  modelName <- tempModel$name
  nameList[i+1] <- paste(tempModel$name, "Chi^2", round(tempModel$output$minimum - satlnL, 2))
  if(MZ) {
    counts[i+1,] <- tempModel$MZ.MZExpectedFrequencies@result * sum(MZObserved)}
  else {
    counts[i+1,] <- tempModel$DZ.DZExpectedFrequencies@result * sum(DZObserved)}
}
barplot(counts,
  main=title,
  xlab="Pair Type",
  col=rainbow(nModels+1, s = 1, v = 1, start = 0, end = max(1,nModels)/(nModels+1), alpha = 1),
  legend = nameList, beside=TRUE,
  args.legend = list(x = "top"))
}

comorbidBarplot(list(DOCModelFit,DOCModelBcausesARun, DOCModelMutualRun, AltFormsDiffThreshRun, RandomMultiiformityRun), mzFreqs, dzFreqs)
```

Comorbidity Model Fits



Alternate forms: One underlying continuum



Alternate forms: Detail of pairs

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = LL + 2(1-p)(1-r)UL + (1-p)^2(1-r)^2UU \quad (30)$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, B2) = r(1-p)LU + (1-p)^2r(1-r)^2UU \quad (31)$$

$$P(\bar{A}1, \bar{B}1, A2, \bar{B}2) = p(1-r)LU + p(1-p)(1-r)^2UU \quad (32)$$

$$P(\bar{A}1, \bar{B}1, A2, B2) = prLU + p(1-p)r(1-r)UU \quad (33)$$

$$P(\bar{A}1, B1, \bar{A}2, B2) = (1-p)^2r^2UU \quad (34)$$

$$P(\bar{A}1, B1, A2, \bar{B}2) = p(1-p)r(1-r)UU \quad (35)$$

$$P(\bar{A}1, B1, A2, B2) = p(1-p)r^2UU \quad (36)$$

$$P(A1, \bar{B}1, A2, \bar{B}2) = p^2(1-r)^2UU \quad (37)$$

$$LL_\lambda = \int_{-\infty}^{\omega_{1A}} \int_{-\infty}^{\omega_{1A}} \phi(R_{A1}, R_{A2}) dR_{A2} dR_{A1} \quad (24)$$

$$LM_\lambda = \int_{-\infty}^{\omega_{1A}} \int_{r_{1A}}^{\omega_{2A}} \phi(R_{A1}, R_{A2}) dR_{A2} dR_{A1} \quad (25)$$

$$LU_\lambda = \int_{-\infty}^{\omega_{1A}} \int_{\omega_{2A}}^{\infty} \phi(R_{A1}, R_{A2}) dR_{A2} dR_{A1} \quad (26)$$

$$MM_\lambda = \int_{r_{1A}}^{\omega_{2A}} \int_{r_{1A}}^{\omega_{2A}} \phi(R_{A1}, R_{A2}) dR_{A2} dR_{A1} \quad (27)$$

$$MU_\lambda = \int_{r_{1A}}^{\omega_{2A}} \int_{\omega_{2A}}^{\infty} \phi(R_{A1}, R_{A2}) dR_{A2} dR_{A1} \quad (28)$$

$$UU_\lambda = \int_{\omega_{2A}}^{\infty} \int_{\omega_{2A}}^{\infty} \phi(R_{A1}, R_{A2}) dR_{A2} dR_{A1} \quad (29)$$

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

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

OpenMx Script Algebra for Alternate Forms

```
# Program: Alternate Forms
```

```
require(OpenMx)
```

```
nv<-1
```

```
# Fit Alternate Forms Model with Cell Frequencies Input, ACE.one overall Threshold
```

```
# -----
```

```
AltFormsModel <- mxModel("AlternateForms",
```

```
  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"),
```

OpenMx Script algebra for

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

OpenMx Script algebra for

```
# 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*R,
  bothAbove*P*S*P*S,
  2*bothAbove*P*S*P*R,
  bothAbove*P*R*P*R
), name="MZExpectedFrequencies"),
```

OpenMx Script algebra for

```
# 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*Q*Q*R*R,
  2*bothAboveDZ*P*Q*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="MZalgebra"),
    mxAlgebraObjective("MZalgebra")),
```

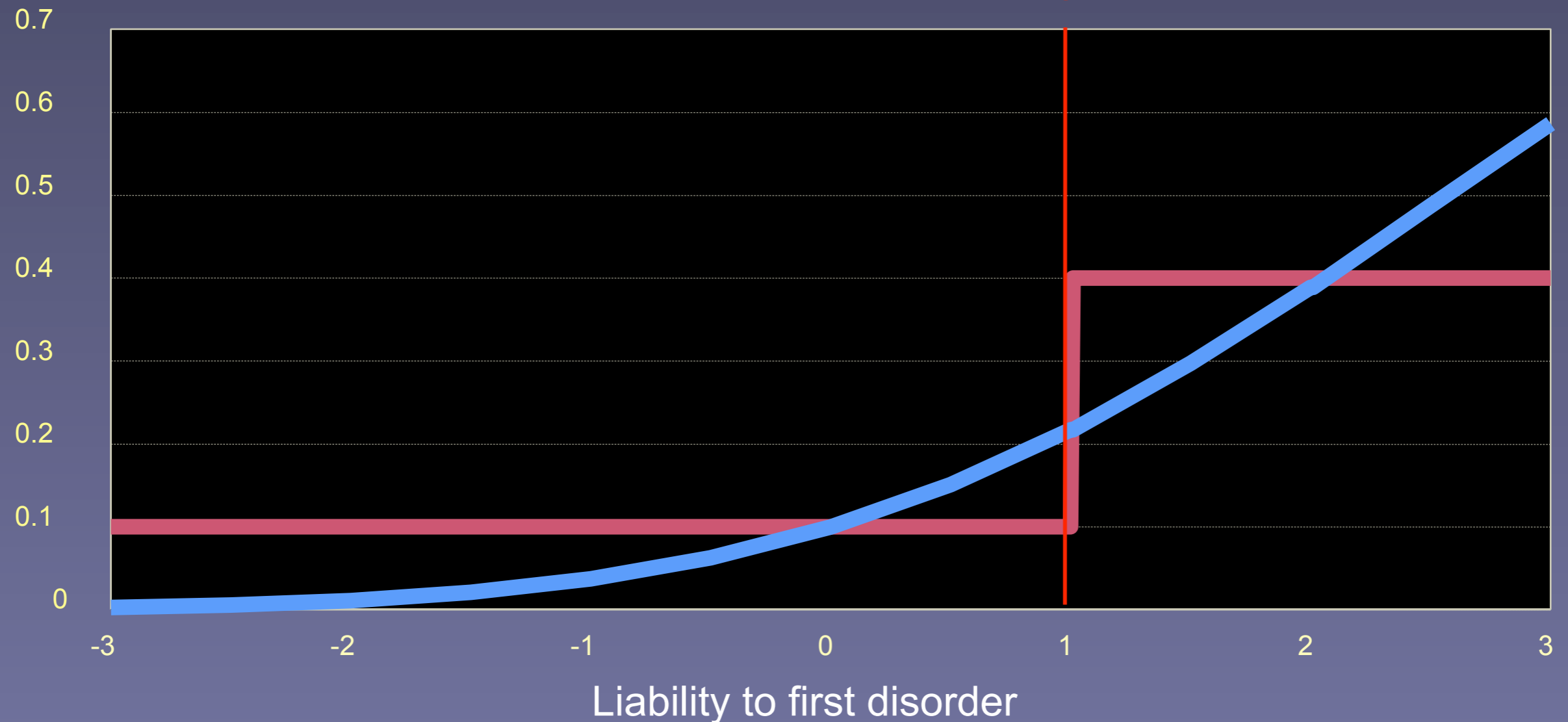
OpenMx Script algebra for

```
mxModel("DZ",
  mxMatrix(type="Full", nrow=10, ncol=1, free=F, values=c(58,18,27,44,7,6,33,15,38,81),
    name="DZObservedFrequencies"),
  mxAlgebra(
    -2 * sum(DZObservedFrequencies *
      log (ACE.DZExpectedFrequencies)), name="DZalobj"),
  mxAlgebraObjective("DZalobj"),
  mxAlgebra( MZ.objective + DZ.objective, name="-2sumll" ),
  mxAlgebraObjective("-2sumll"))

AltFormsRun<-mxRun(AltFormsModel)
summary(AltFormsRun)
```

Alternative models of increasing risk to a second disorder

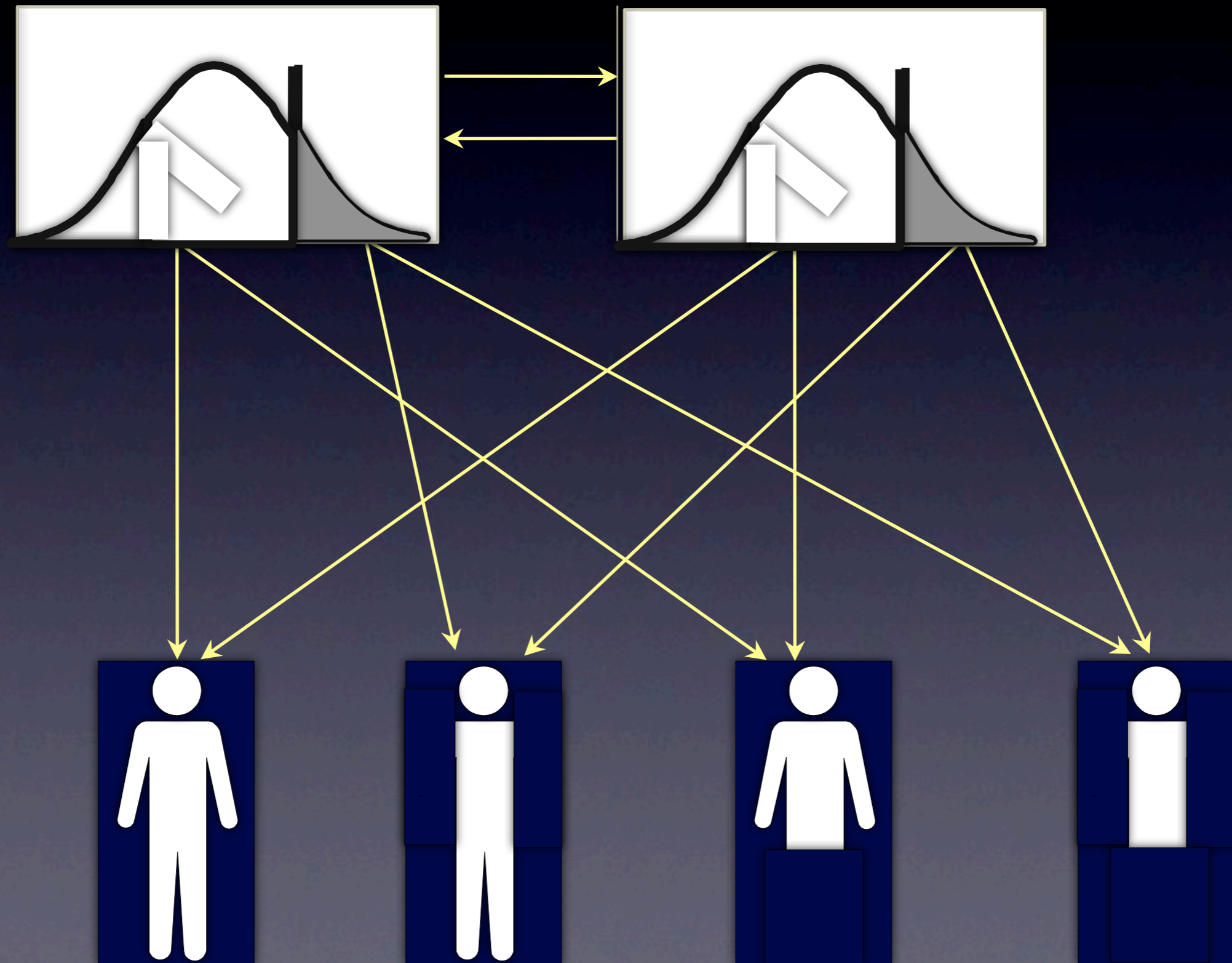
$p(\text{comorbid}) = \text{chance of getting second disorder}$



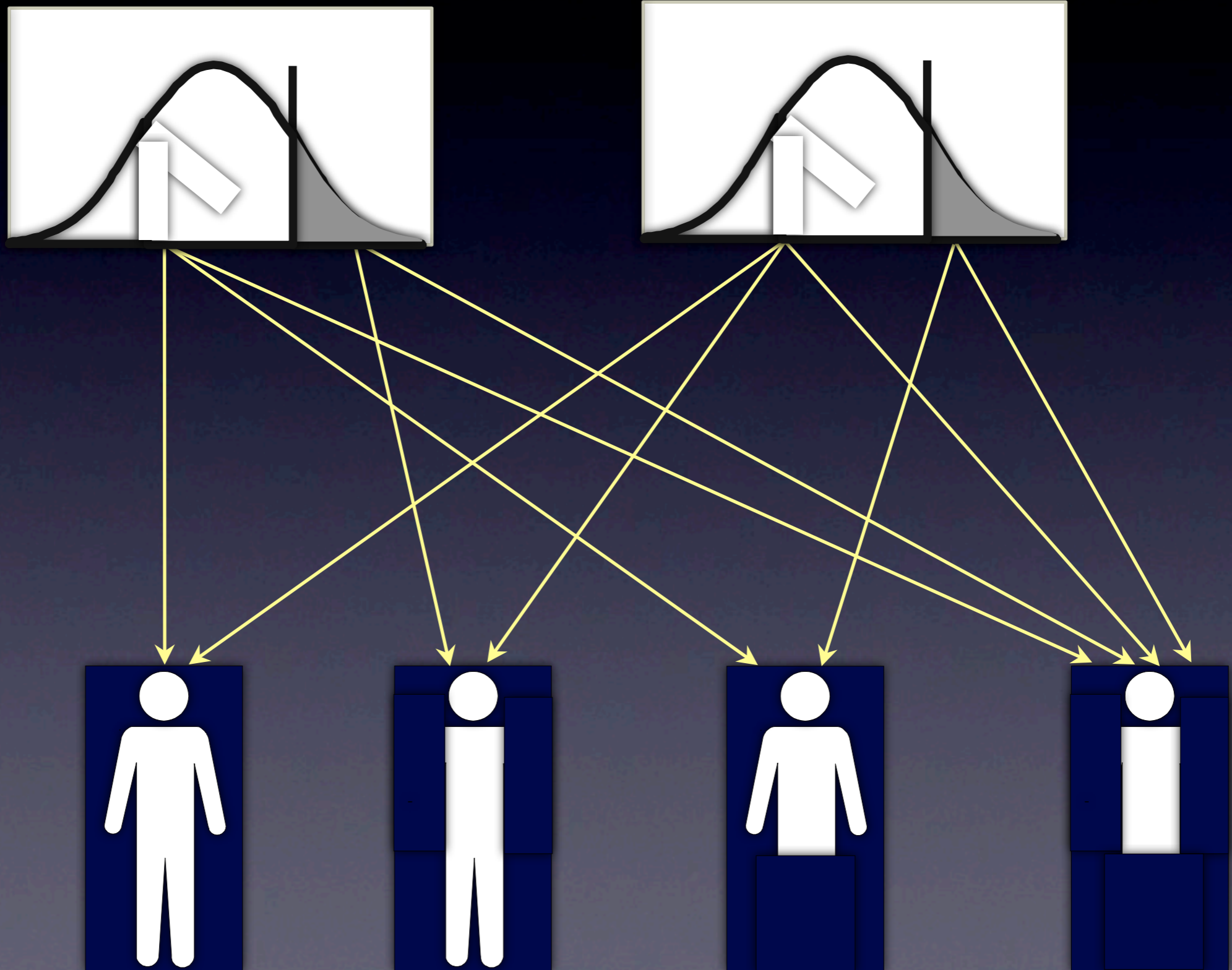
— Causal/Correlational/Alternate Model — Jump Model

Threshold Model $r=.5$

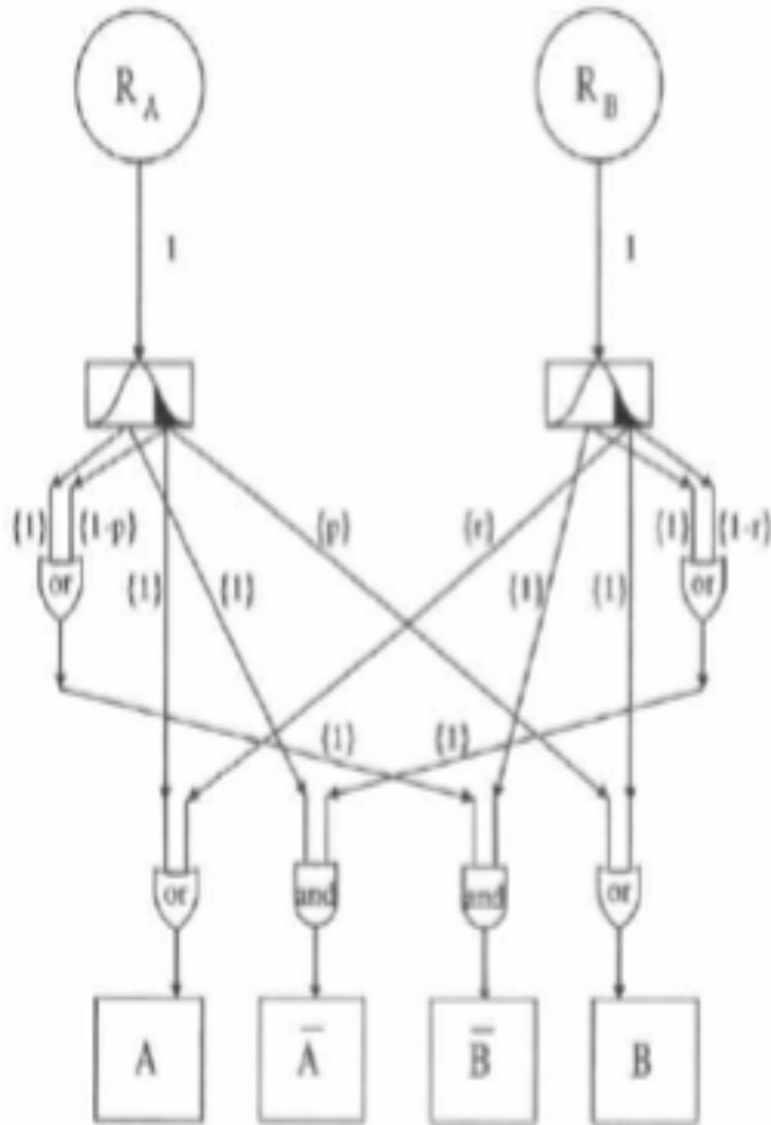
Causal or correlated models



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



Random Multififormity: Detail



R - Risk factors

A - Disease A



- Threshold Filtration process



Or operation: A arises when LA or with probability r if LB is above threshold



And operation: not A arises when LA is below threshold and LB are above threshold

$$P(\bar{A}, \bar{B}) = L_A \cdot L_B \quad (8)$$

$$P(\bar{A}, B) = (1 - r)L_A \cdot U_B \quad (9)$$

$$P(A, \bar{B}) = U_A \cdot (1 - p)L_B \quad (10)$$

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

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = LL_A \cdot LL_B \quad (40)$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, B2) = LL_A \cdot (1 - r)LU_B \quad (41)$$

$$P(\bar{A}1, \bar{B}1, A2, \bar{B}2) = (1 - p)LU_A \cdot LL_B \quad (42)$$

$$P(\bar{A}1, \bar{B}1, A2, B2) = LU_A \cdot (pLL_B + LU_B) + LL_A \cdot rLU_B \quad (43)$$

$$P(\bar{A}1, B1, \bar{A}2, B2) = LL_A \cdot (1 - r)^2 UU_B \quad (44)$$

$$P(\bar{A}1, B1, A2, \bar{B}2) = (1 - p)LU_A \cdot (1 - r)LU_B \quad (45)$$

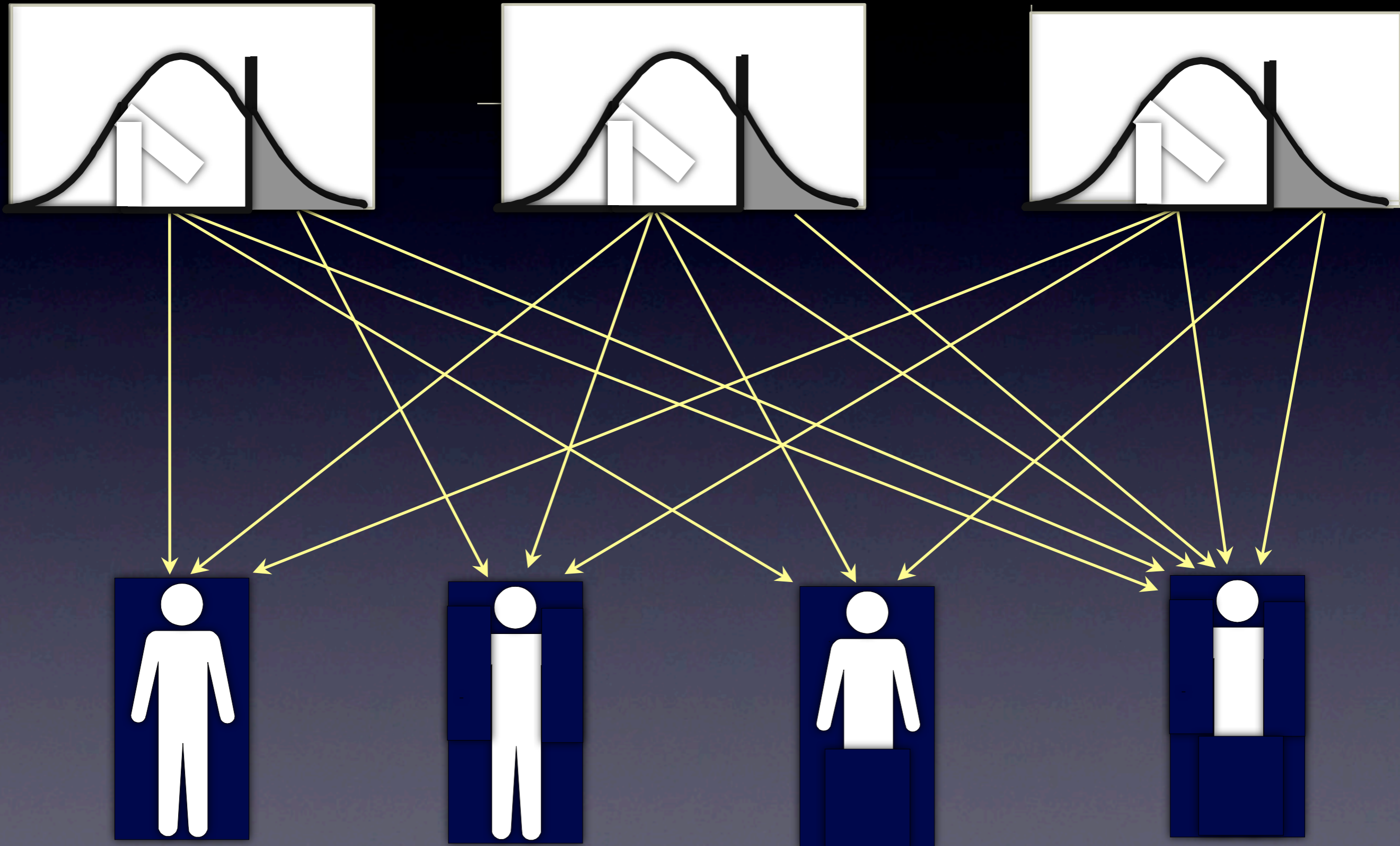
$$P(\bar{A}1, B1, A2, B2) = (1 - r)LU_A \cdot (pLU_B + UU_B) + LL_A \cdot rLL_B \quad (46)$$

$$P(A1, \bar{B}1, A2, \bar{B}2) = (1 - p)^2 UU_A \cdot LL_B \quad (47)$$

$$P(A1, \bar{B}1, A2, B2) = UU_A \cdot (p(1 - p)LL_B + (1 - p)LU_B) + (1 - p)LU_A \cdot rLU_B \quad (48)$$

$$P(A1, B1, A2, B2) = p^2 UU_A \cdot LL_B + 2p UU_A \cdot LU_B + UU_A \cdot UU_B + LU_A \cdot 2r UU_B + 2p LU_A \cdot r LU_B + LL_A \cdot r^2 UU_B. \quad (49)$$

Three separate disorders



Three Independent Disorders

$$P(\bar{A}1, \bar{B}1, \bar{A}2, \bar{B}2) = LL_A \cdot LL_{AB} \cdot LL_B \quad (60)$$

$$P(\bar{A}1, \bar{B}1, \bar{A}2, B2) = LL_A \cdot LL_{AB} \cdot LU_B \quad (61)$$

$$P(\bar{A}1, \bar{B}1, A2, \bar{B}2) = LU_A \cdot LL_{AB} \cdot LL_B \quad (62)$$

$$P(\bar{A}1, \bar{B}1, A2, B2) = L_A \cdot LL_{AB} \cdot LL_B + LU_A \cdot LL_{AB} \cdot LU_B \quad (63)$$

$$P(\bar{A}1, B1, \bar{A}2, B2) = LL_A \cdot LL_{AB} \cdot UU_B \quad (64)$$

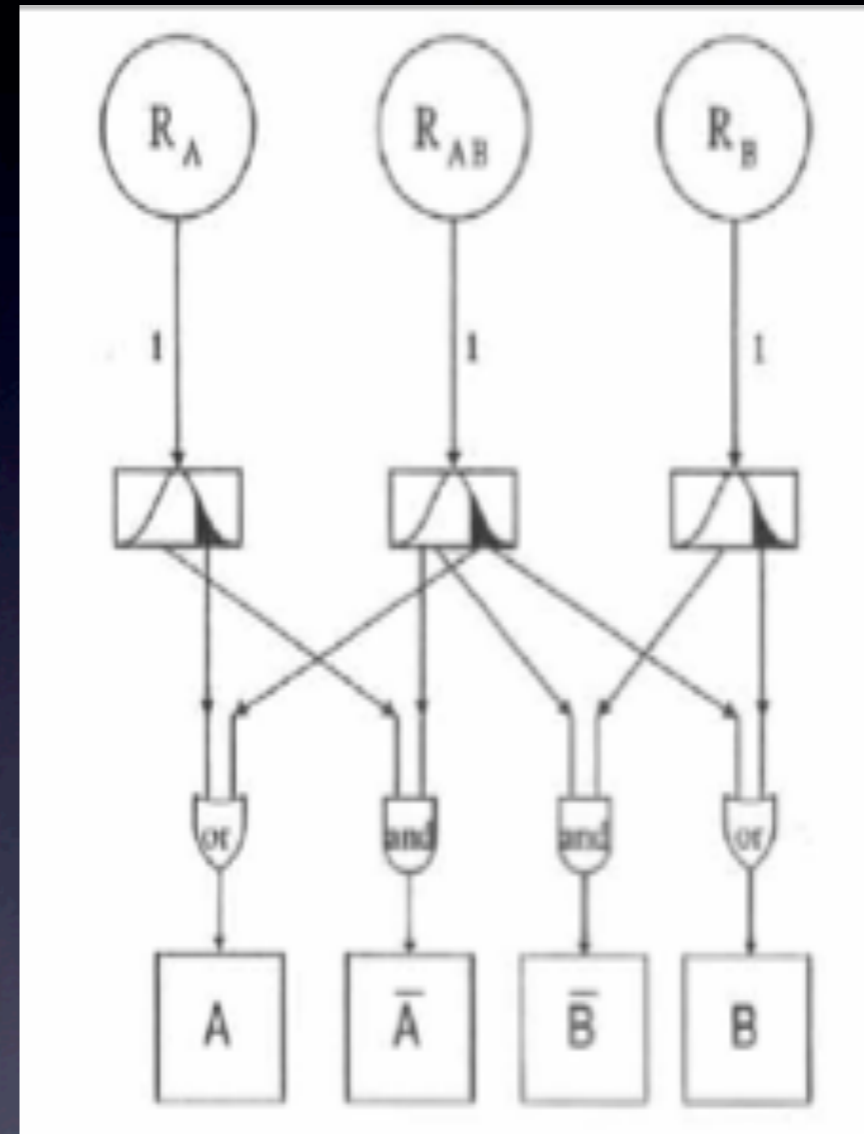
$$P(\bar{A}1, B1, A2, \bar{B}2) = LU_A \cdot LL_{AB} \cdot LU_B \quad (65)$$

$$P(\bar{A}1, B1, A2, B2) = L_A \cdot LU_{AB} \cdot U_B + LU_A \cdot LL_{AB} \cdot UU_B \quad (66)$$

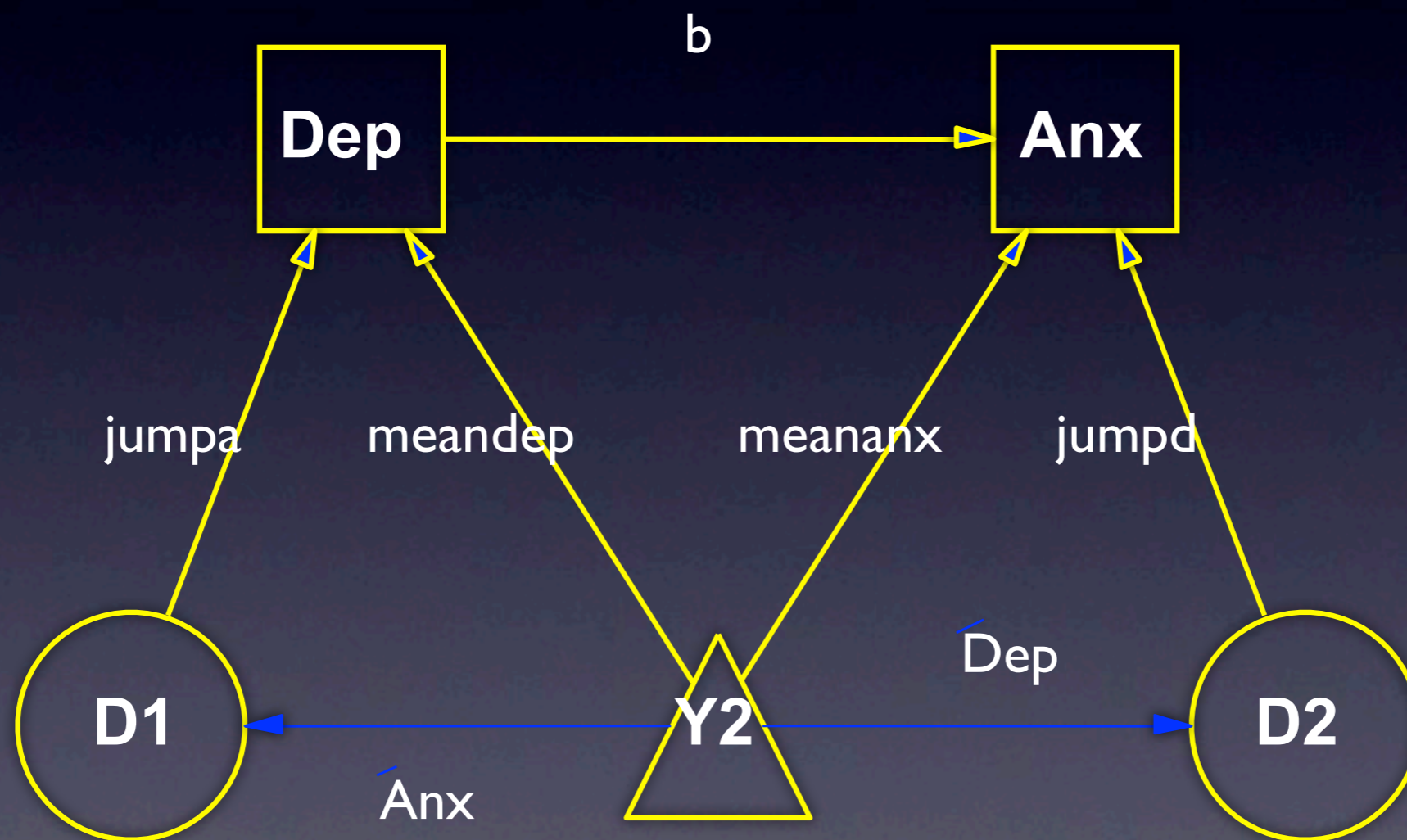
$$P(A1, \bar{B}1, A2, \bar{B}2) = UU_A \cdot LL_{AB} \cdot LL_B \quad (67)$$

$$P(A1, \bar{B}1, A2, B2) = L_A \cdot LU_{AB} \cdot L_B + UU_A \cdot LL_{AB} \cdot LU_B \quad (68)$$

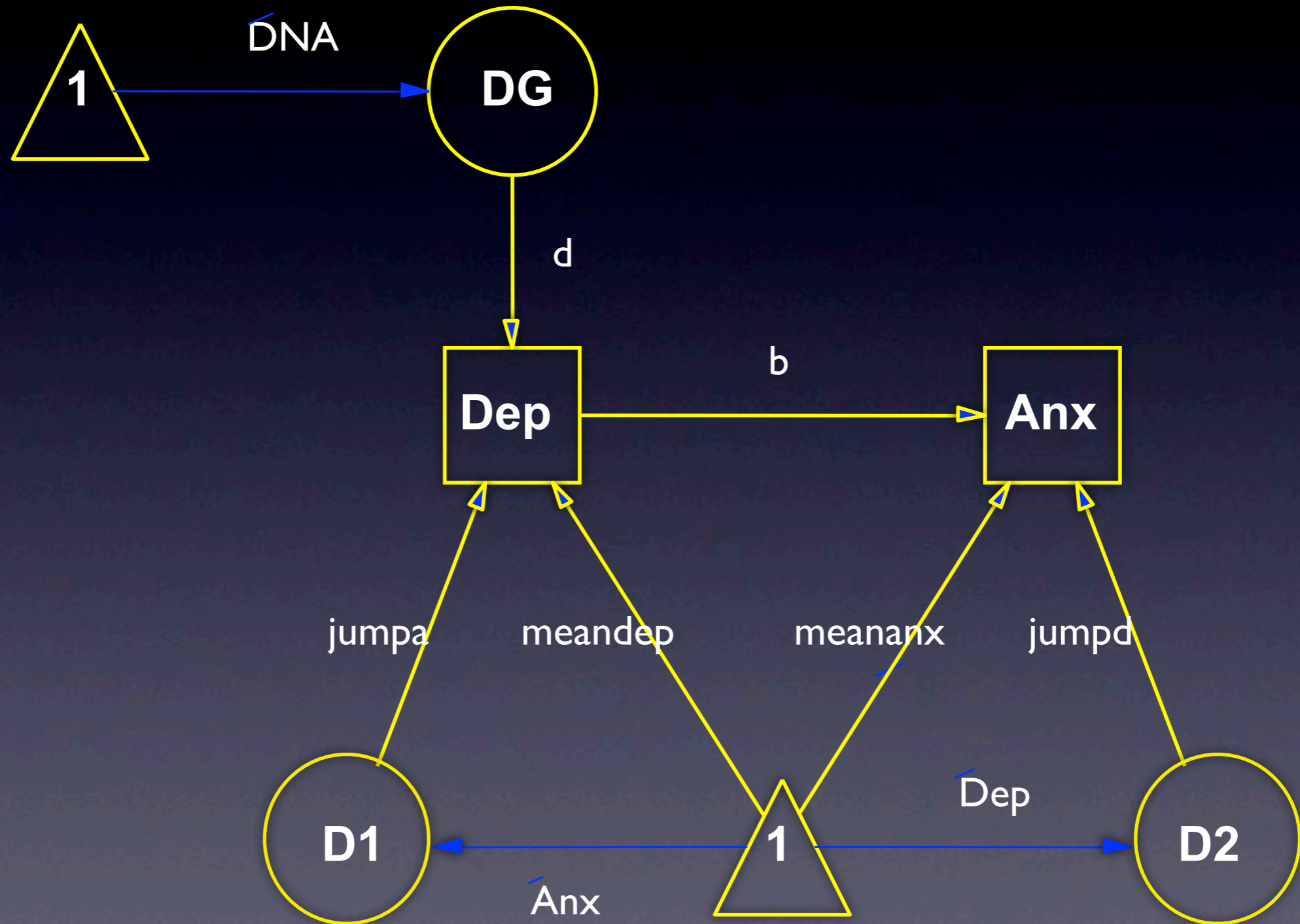
$$P(A1, B1, A2, B2) = UU_{AB} + UU_A \cdot LL_{AB} \cdot UU_B + 2U_A \cdot LU_{AB} \cdot U_B \quad (69)$$



Unified Comorbidity Model?



Unified Genetic Comorbidity Model?



Sources for comorbidity scripts

- <http://ibgwww.colorado.edu/cadd/software>
- 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

- <http://www.vcu.edu/mx/examples>
- Mike Neale's script website.
- More than a little bit dusty

OpenMx User-defined Functions

- Can specify AlgebraObjective

```
mxAlgebra( MZ.objective + DZ.objective, name="-2sum11" ),  
mxAlgebraObjective("-2sum11"))
```

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

Comorbidity with Covariates

- Soo Rhee's website again
- <http://ibgwww.colorado.edu/cadd/software>
- 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