Correction for Ascertainment

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Ascertainment Examples

- Studies of patients and controls
- Patients and relatives
 - Twin pairs with at least one affected
 - Single ascertainment pi → 0
 - Complete ascertainment pi = 1
 - Incomplete 0 < pi <1
- Linkage studies
 - Affected sib pairs, DSP etc
 - Multiple affected families

Likelihood approach

Advantages & Disadvantages

- Usual nice properties of ML remain
- Flexible
- Simple principle
 - Consideration of possible outcomes
 - Re-normalization
- May be difficult to compute

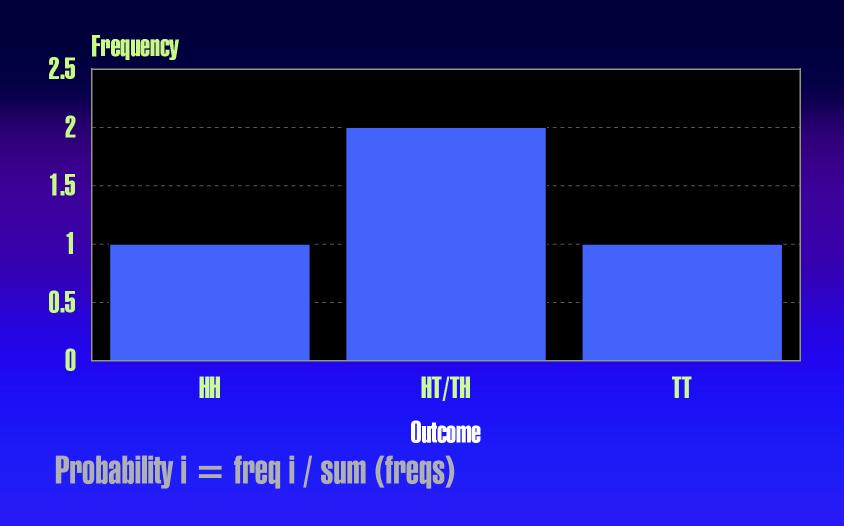
Maximum Likelihood Estimates

Have nice properties

- Asymptotically unbiased
- Minimum variance of all asymptotically unbiased estimators
- Invariant to transformations

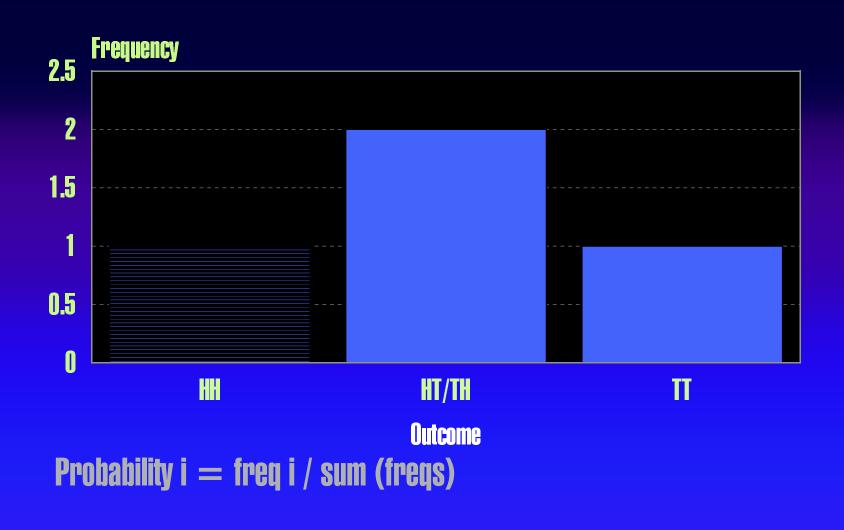
Example: Two Coin Toss

3 outcomes



Example: Two Coin Toss

3 outcomes



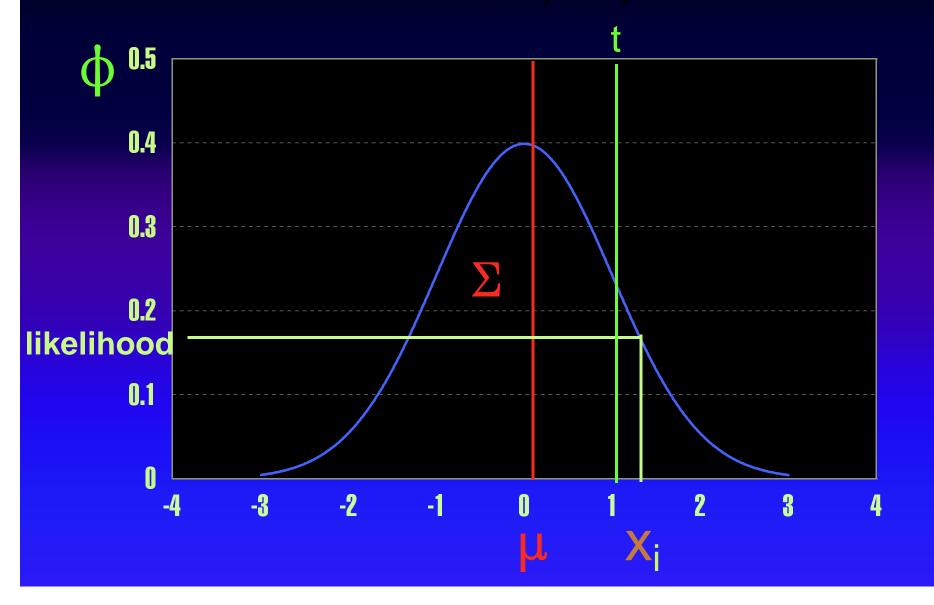
Non-random ascertainment

Example

- Probability of observing TT globally
 - $\overline{-1}$ outcome from 4 = 1/4
- Probability of observing TT if HH is not ascertained
 - -1 outcome from 3 = 1/3
 - or 1/4 divided by 'ascertainment correction' of 3/4 = 1/3

Correcting for ascertainment

Univariate continuous case; only subjects > t ascertained



Correcting for ascertainment

Dividing by the realm of possibilities

• Without ascertainment, we compute pdf, $\phi(\mu_{ij}, \Sigma_{ij})$, at observed value X_i divided by:

$$\int_{-\infty}^{\infty} \varphi(\mu_{ij}, \Sigma_{ij}) dx = 1$$

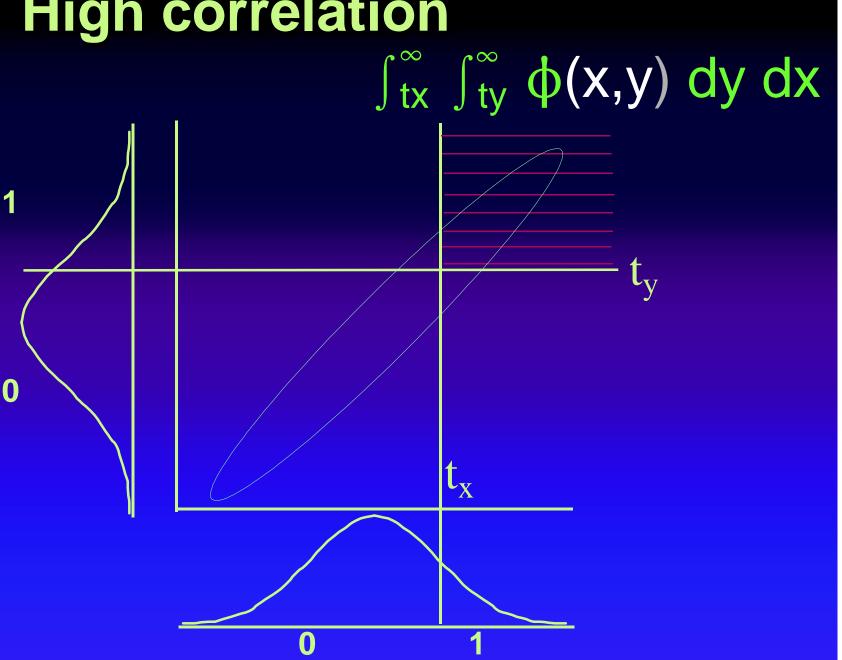
With ascertainment, the correction is

$$\int_{t}^{\infty} \varphi(\mu_{ij}, \Sigma_{ij}) dx = 1 - \int_{-\infty}^{t} \varphi(\mu_{ij}, \Sigma_{ij}) dx$$

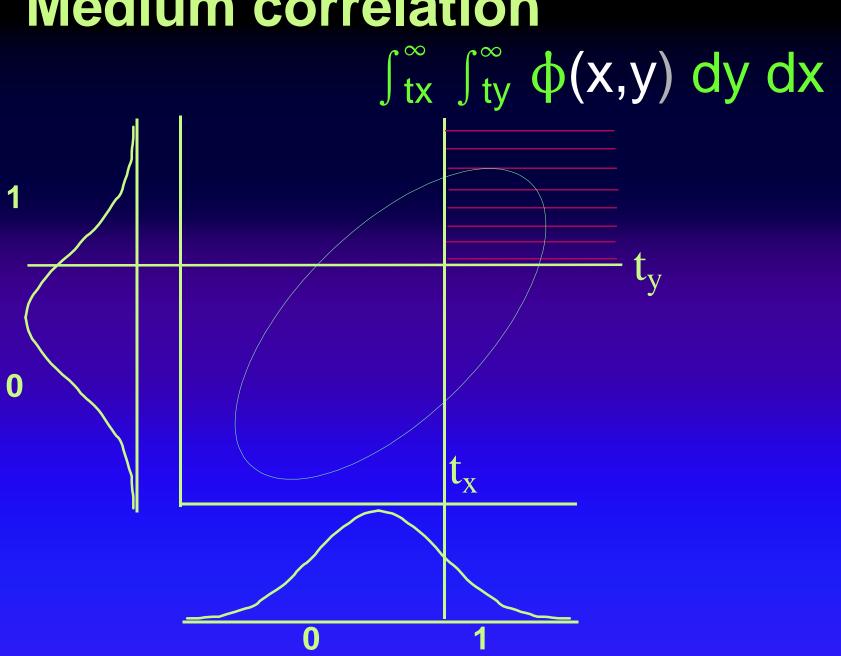
Correction depends on model

- 1 Correction independent of model parameters: "sample weights"
- 2 Correction depends on model parameters: weights vary during optimization
- In twin data almost always case 2
 - continuous data
 - binary/ordinal data

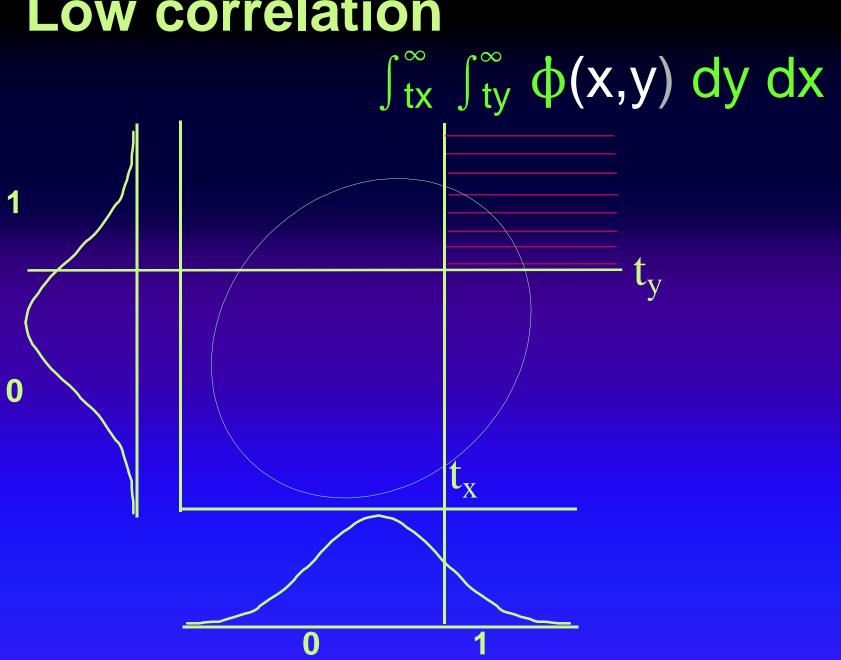
High correlation



Medium correlation



Low correlation



Two approaches for twin data

- Contingency table approach
 - Automatic
 - Limited to two variable case
- Raw data approach
 - Manual
 - Multivariate
 - Moderator / Covariates

Contingency Table Case

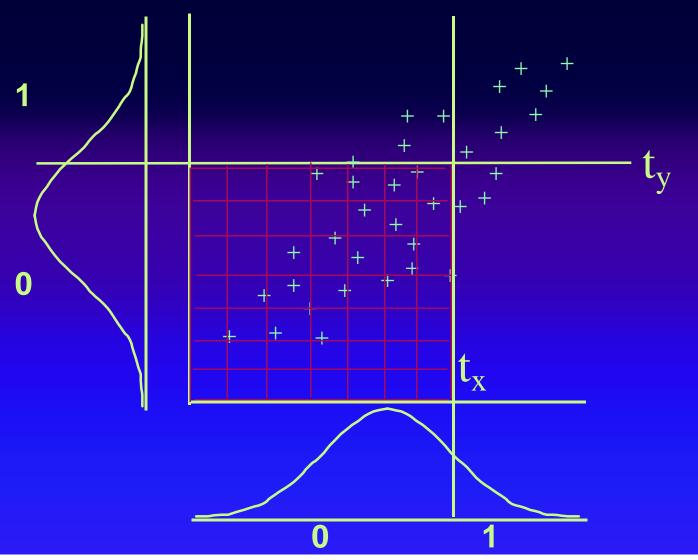
Binary data

- Feed program contingency table as usual
- Use -1 for frequency for non-ascertained cells
- Correction for ascertainment handled automatically

At least one twin affected

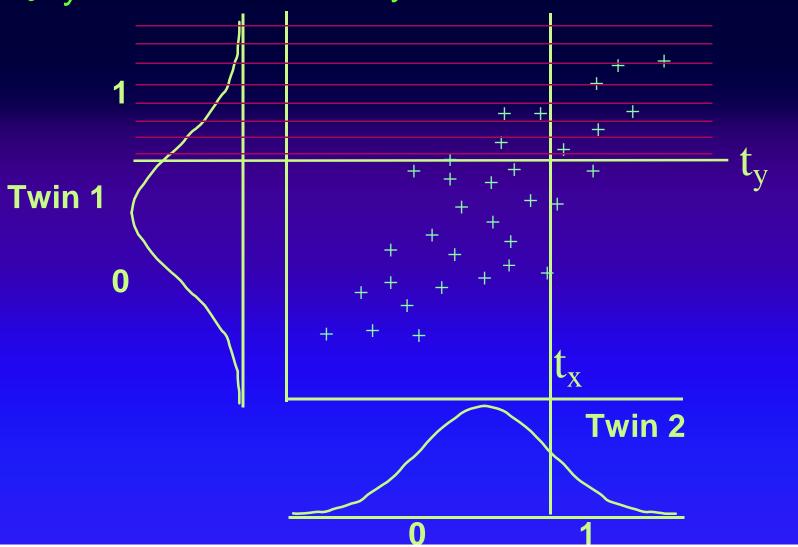
Ascertainment Correction

 $1-\int_{-\infty}^{tx} \int_{-\infty}^{ty} \varphi(x,y) \, dy \, dx$



Ascertain iff twin 1 > t

$$\int_{ty}^{\infty} \varphi(y) dy = \int_{ty}^{\infty} \int_{-\infty}^{\infty} \varphi(x,y) dx dy$$



Contingency Tables

- Use -1 for cells not ascertained
- Can be used for ordinal case
- Need to start thinking about thresholds
 - Supply estimated population values
 - Estimate them jointly with model

Classical Twin Study: Contingency Table ftp://views.vcu.edu/pub/mx/examples/ncbook2/categor.mx

```
G1: Model parameters
Data Calc NGroups=4
Begin Matrices;
X Lower 1 1 Free
Y Lower 1 1 Free
Z Lower 1 1 Free
W Lower 1 1
End Matrices;
! parameters are fixed by default, unless declared free
Begin Algebra;
A = X^*X';
C = Y^*Y';
 E = Z^*Z';
D= W*W';
End Algebra:
End
```

Group 2

Group 3

```
G3: young female DZ twin pairs
Data Ninput=2
CTable 2 2
201 94
82 63
Begin Matrices = Group 1
H Full 1 1
Q Full 1 1
T Full 2 1 Free
End Matrices;
Matrix H.5
Matrix Q .25
Start .6 All
Covariances A+C+D+E | H@A+C+Q@D_
       H@A+C+Q@D | A+C+D+E /
Thresholds T;
Options RSidual NDecimals=4
End
```

Group 4

```
Group 4: constrain variance to 1
Constraint NI=1
Begin Matrices = Group 1;
I unit 1 1
End Matrices;

Constraint I = A+C+E+D;
Option Multiple
End
Specify 2 t 8 9
Specify 3 t 8 9
End
```

Raw data approach

- Correction not always necessary
 - ML MCAR/MAR
 - Prediction of missingness
- Correct through weight formula

Types of missingness

Little & Rubin Terminology

- MCAR: Missing completely at random
- MAR: Missing at random
- NMAR: Not missing at random

Simulation Example

- Selrand: MCAR
 - missingness function of independent random variable
- Selonx: MAR
 - missingness predicted by other measured variable in analysis + MCAR
- Selony: NMAR
 - missingness mechanism related to "residual" variance in dependent variable

Method

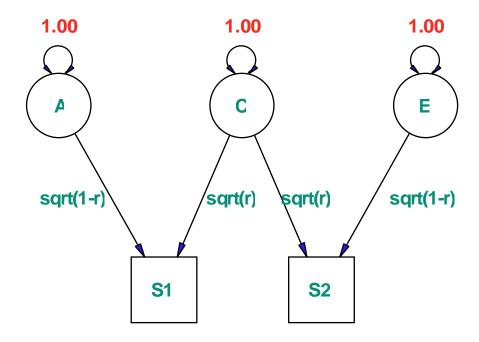
- Simulate bivariate normal data X,Y
 - Sigma = 1.5
 - **-** .5 1
 - Mu = 0, 0
- Make some variables missing
 - Generate independent random normal variable, Z, if Z>0 then Y missing
 - If X>0 then Y missing
 - If Y>0 then Y missing
- Estimate elements of Sigma & Mu
- Constrain elements to population values 1,.5, 0 etc
- Compare fit
- Ideally, repeat multiple times and see if expected 'null' distribution emerges

SAS simulation script

```
OPTIONS nocenter;
FILENAME sibs 'selonx.rec';
DATA NEALE1;
FILE sibs;
array v{2};
x = .5;
n=0:
sample: IF N gt 500 THEN GO TO DONE;
n=n+1;
famfac=rannor(0);
v(1)=SQRT(X)*famfac + SQRT(1-X)*RANNOR(0);
if rannor(0) gt 0 then do;
 v(2) = SQRT(X)*famfac + SQRT(1-X)*RANNOR(0);
 size=2:
 end;
else do:
 v(2)=.;
 size=1;
end;
PUT v(1) v(2);
OUTPUT:
x1=v\{1\}; y=v\{2\};
GO TO sample;
```

DONE: COMMENT sample complete;

SAS simulation 'model'



Mx Script

Rather basic, like Monday morning

```
Estimate pop cov matrix of X&Y, with Y observed iff X>0
Data ng=1 ni=2
Rectangular file=selonx.rec
Begin Matrices;
 a sy 2 2 free! covariance of x,y
 m fu 1 2 free! mean of x,y
End Matrices:
Means M /
Covariance A /
 matrix a 1.31
 bound .1 2 a 1 1 a 2 2
 option rs mu
Option issat
end
fix all
 matrix 1 a
1.51
matrix 1 m
00
end
```

Mx Scripts & Data

F:\mcn\2004\sel

- Check output:
 - Summary statistics (obs means)
 - Estimated means & covariance matrices
 - Difference in fit between estimated values and population values
- Interpretation?

ML estimation under different missingness mechanisms

Missingness	mean x	mean y	var x	cov xy	var y	LR Chisq
MCAR (rand) MLE						
<sample></sample>						
MAR (on x) MLE						
<sample></sample>						
NMAR (on y) MLE						
<sample></sample>						

ML estimation under different missingness mechanisms

Missingness	mean x	mean y	var x	cov xy	var y	LR Chisq
MCAR (rand) MLE	-0.0116	-0.1	1.0505	0.4998	0.8769	6.492
sample	-0.0116	-0.0919	1.0505		0.8839	
MAR (on x) MLE	0.0048	0.0998	1.0084	0.4481	1.1025	5.768
sample	0.0014	0.4437	1.0084		0.9762	
NMAR (on y) MLE	-0.0204	0.6805	0.9996	0.1356	0.2894	227.262
sample	0.0448	0.7373	0.9996		0.2851	

Screen + Examination

Only a subset, selected on basis of screen, are examined

- Bivariate analysis of screen & exam
 - No ascertainment correction required
 - Example: all pairs where at least one screens positive are examined
 - Works for continuous & ordinal
- Undersampling: some proportion of pairs concordant negative for screen are also examined
 - Ascertainment correction required
 - Different correction for screen -- vs +-/-+/++

Normal Theory Likelihood Function

For raw data in Mx

In
$$L_i = f_i$$
 In $\left[\sum_{j=1}^m w_j \ g(x_i, \mu_{ij}, \sum_{ij})\right]$

- x_i vector of observed scoreson n subjects
- μ_{ij} vector of predicted means
- Σ_{ii} matrix of predicted covariances
 - functions of parameters

Likelihood Function Itself

The guts of it

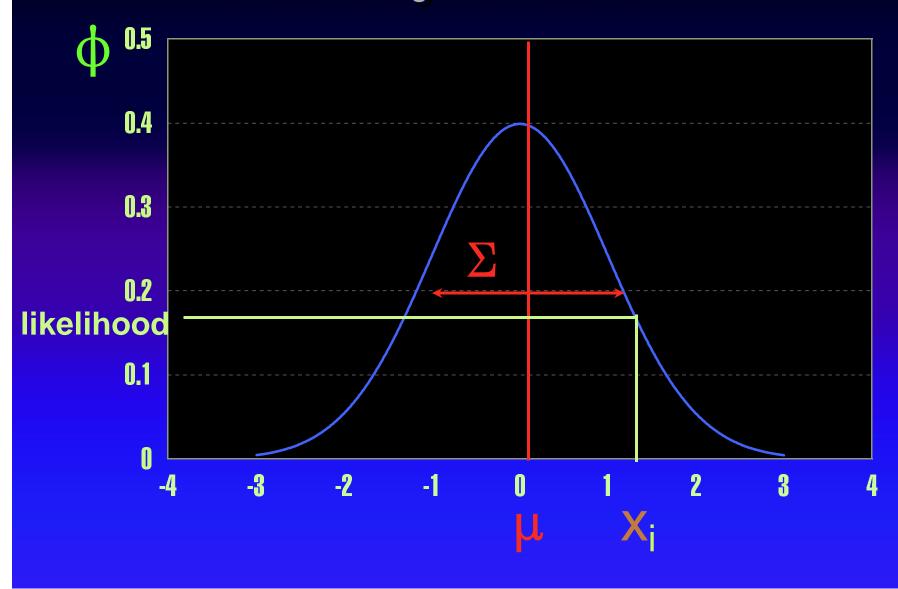
In
$$L_i = f_i$$
 In $\left[\sum_{j=1}^{m} w_{ij} g(x_i, \mu_{ij}, \sum_{ij})\right]$

 $g(x_i, \mu_{ij}, \Sigma_{ii})$ - likelihood function

Example: Normal pdf

Normal distribution $\phi(\mu_{ij}, \Sigma_{ij})$

Likelihood is height of the curve



Weighted mixture of models

Finite mixture distribution

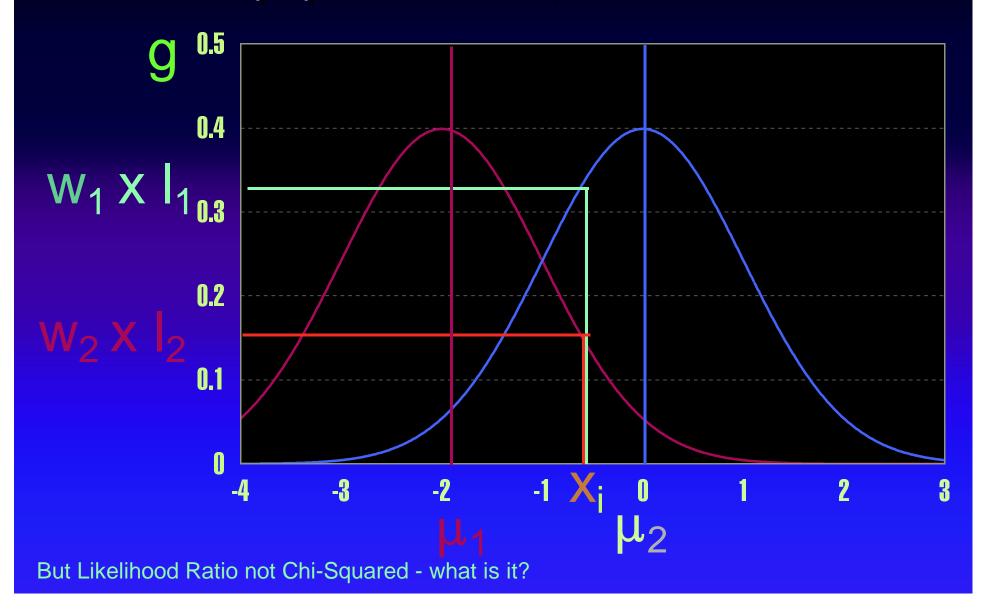
In
$$L_i = f_i$$
 In $\sum_{j=1}^{m} w_{ij} g(x_i, \mu_{ij}, \Sigma_{ij})$

j = 1....m models w_{ij} Weight for subject i model j

e.g., Segregation analysis

Mixture of Normal Distributions

Two normals, propotions w1 & w2, different means



General Likelihood Function

Finally the frequencies

In
$$L_i = f_i$$
 In $\sum_{j=1}^{m} w_j g(x_i, \mu_{ij}, \Sigma_{ij})$

f_i - frequency of case i

- Sample frequencies binary data
- Sometimes 'sample weights'
- Might also vary over model j

General Likelihood Function

Things that may differ over subjects

In
$$L_i = f_i \ln \left[\sum_{j=1}^m w_{ij} g(x_i, \mu_{ij}, \sum_{ij}) \right]$$

 $i = 1....n$ subjects (families)

- Model for Means can differ
- Model for Covariances can differ
- Weights can differ
- Frequencies can differ

How do we make things vary?

Definition variables

- Read in rectangular or ordinal data
- Definition command like backwards select
 - Deletes variables to be analyzed
 - Makes them available for individual-based analyses
 - Variable can be placed in any modifiable matrix element

Raw Ordinal Data Syntax

- Read in ordinal file
- May use frequency command to save space
- Weight uses \mnor function
- \mnor(R_M_U_L_K)
 - R covariance matrix (p x p)
 - M mean vector (1xp)
 - U upper threshold (1xp)
 - L lower threshold (1xp)
 - K indicator for type of integration in each dimension (1xp)
 - 0: L=-∞
 - 1: U=+∞
 - **2:** ∫ u
 - 3: L=-∞ U=∞

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Y Lower 1 1 Free
 Z Lower 1 1 Free
 W Lower 1 1
End Matrices;
! parameters are fixed by default, unless declared free
Begin Algebra;
 A = X^*X';
 C= Y*Y';
 E = Z^*Z';
 D= W*W';
End Algebra:
End
```

```
G2: MZ twin pairs
Data Ninput=3
Ordinal File=mz.frq
Labels T1 T2 Freq
Definition Freq;
Begin Matrices= Group 1
T full 2 1 Free
 F full 1 1! Frequency
End Matrices;
Specify F Freq
Covariances A+C+D+E | A+C+D _
       A+C+D | A+C+D+E;
Thresholds T;
Frequency F;
Options RSidual
End
```

```
G3: DZ twin pairs
Data Ninput=3
Labels T1 T2 Freq
Ordinal File=dz.frq
Definition Freq;
```

```
Begin Matrices= Group 1
H Full 1 1
Q Full 1 1
T Full 2 1 Free
F full 1 1! Frequency
End Matrices;
Specify F Freq
Matrix H .5
Matrix Q .25
Start .6 All
```

```
Covariances A+C+D+E | H@A+C+Q@D _ 
H@A+C+Q@D | A+C+D+E / 
Thresholds T;
```

```
Group 4: constrain variance to 1
Constraint NI=1
Begin Matrices = Group 1;
I unit 1 1
End Matrices;

Constraint I = A+C+E+D;
Option Multiple
End
Specify 2 t 8 9
Specify 3 t 8 9
End
```

Ascertainment additional commands

```
Begin Algebra; M=(A+C+E|A+C_A+C|A+C+E); N=(A+C+E|h@A+C_h@A+C|A+C+E); J=I-\mor(M_Z_T_T_Z); !Z=[0\ 0] K=I-\mor(N_Z_T_T_Z); !DZ case End Algebra;
```

Weight J~; ! for MZ group Weight K~; ! DZ group

Correcting for ascertainment

Linkage studies

- Multivariate selection: multiple integrals
 - double integral for ASP
 - four double integrals for EDAC
- Use (or extend) weight formula
- Precompute in a calculation group
 - -unless they vary by subject

Conclusion

- Be careful when designing studies with non-random ascertainment
- Usually possible to correct
- In principle, heritability should not change
- In practice, it might