

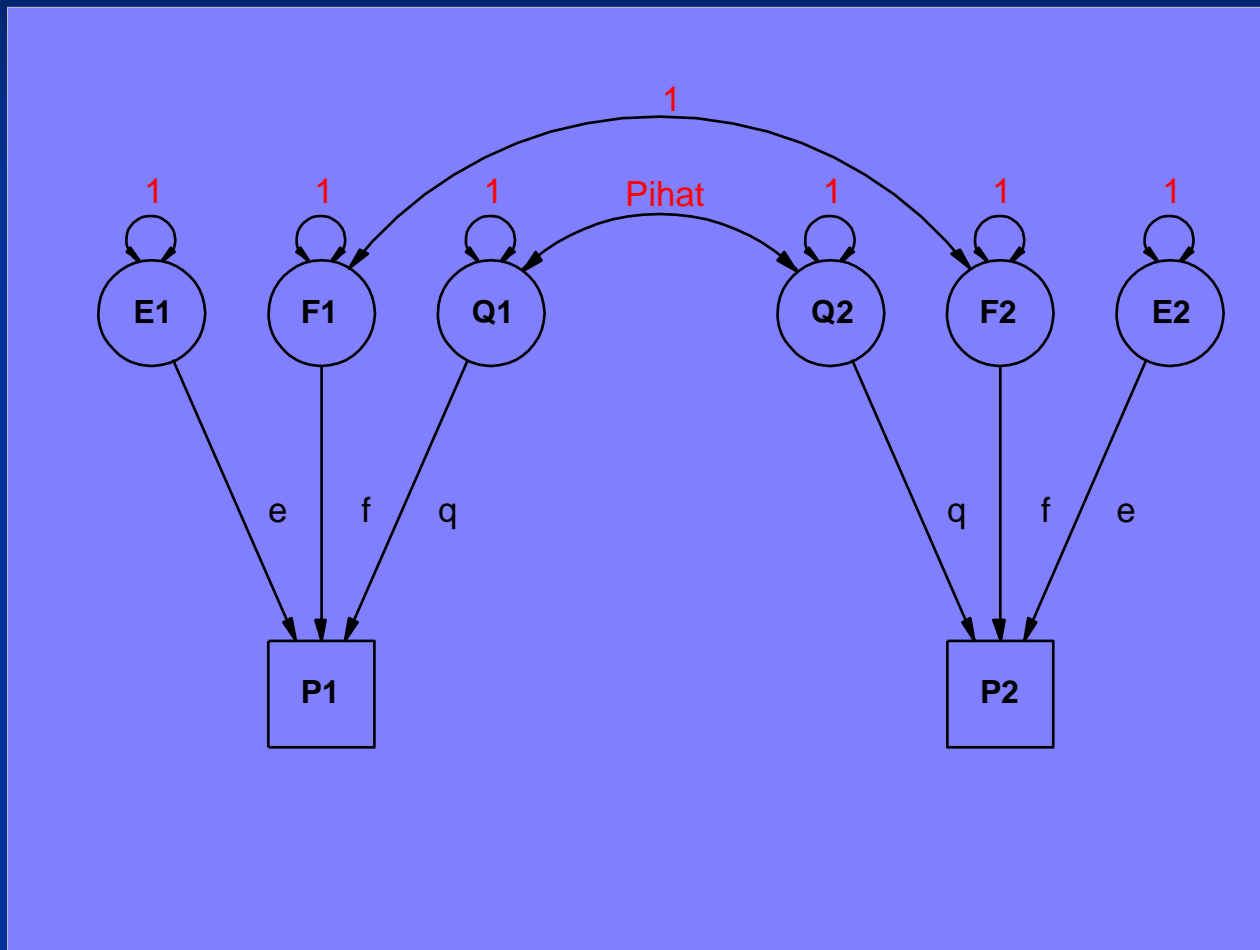
# Linkage in Selected Samples

Boulder Methodology Workshop  
2005

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# Basic Genetic Model

$$P_{ihat} = p(\text{IBD}=2) + .5 p(\text{IBD}=1)$$



Q: QTL Additive Genetic

F: Family Environment

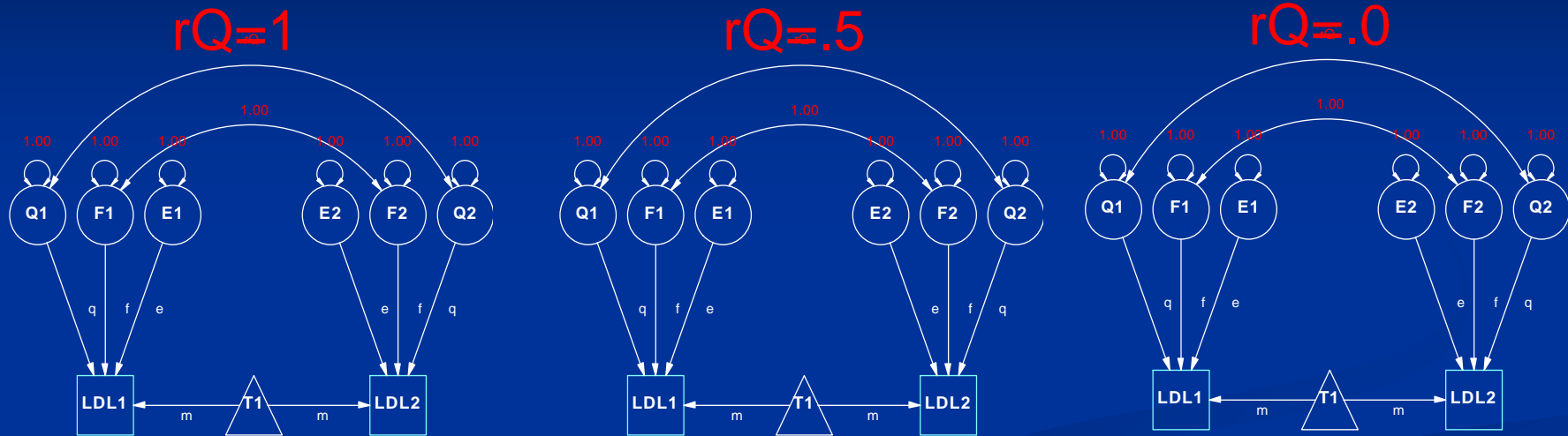
E: Random Environment

3 estimated parameters: q, f and e

Every sibship may have different model

# Mixture distribution model

Each sib pair  $i$  has different set of WEIGHTS



weight $_j$  x Likelihood under model  $j$

$p(\text{IBD}=2) \times P(\text{LDL1 \& LDL2} \mid rQ = 1)$

$p(\text{IBD}=1) \times P(\text{LDL1 \& LDL2} \mid rQ = .5)$

$p(\text{IBD}=0) \times P(\text{LDL1 \& LDL2} \mid rQ = 0)$

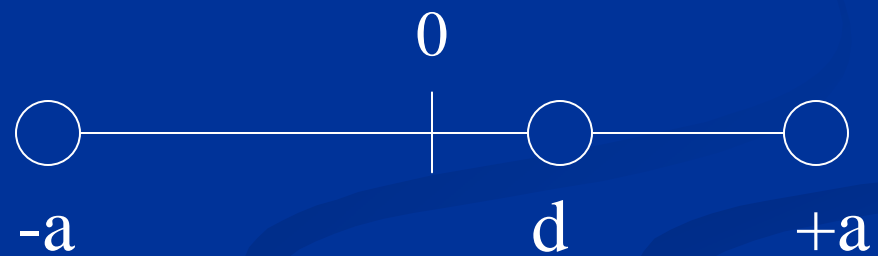
Total likelihood is sum of weighted likelihoods

# QTL's are factors

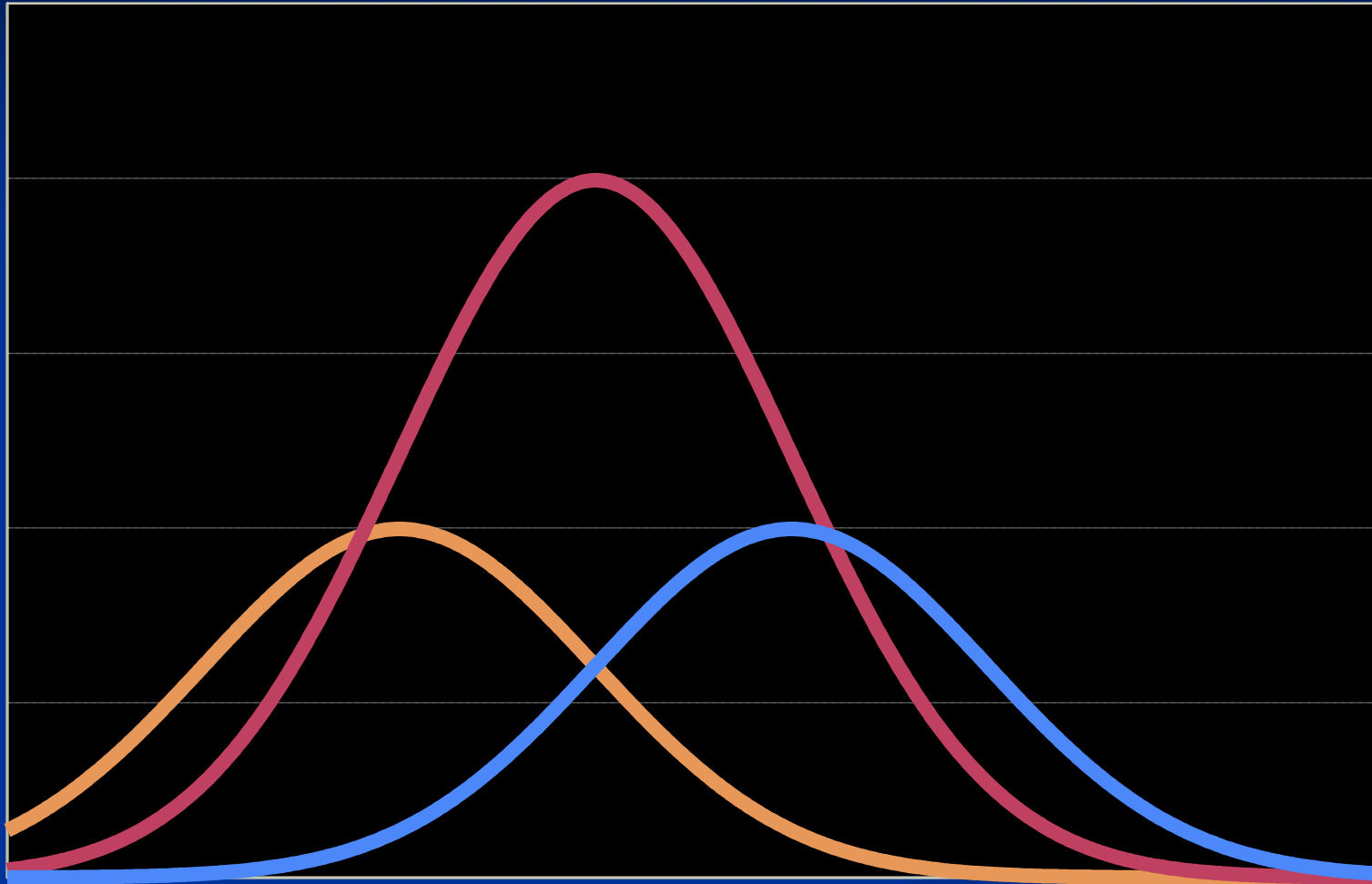
- Multiple QTL models possible, at different places on genome
- A big QTL will introduce non-normality
  - Introduce mixture of means as well as covariances (27ish component mixture)
- Mixture distribution gets nasty for large sibships

# Biometrical Genetic Model

|    | Genotype means |
|----|----------------|
| AA | $m + a$        |
| Aa | $m + d$        |
| aa | $m - a$        |



# Mixture of Normal Distributions



aa



Aa



AA

Equal variances, Different means and different proportions according to allele frequencies

# Implementing the Model

- Estimate QTL allele frequency  $p$
- Estimate distance between homozygotes  
 $2a$
- Compute QTL additive genetic variance as
  - $2pq[a+d(q-p)]^2$
- Compute likelihood conditional on
  - IBD status
  - QTL allele configuration of sib pair (IBS)

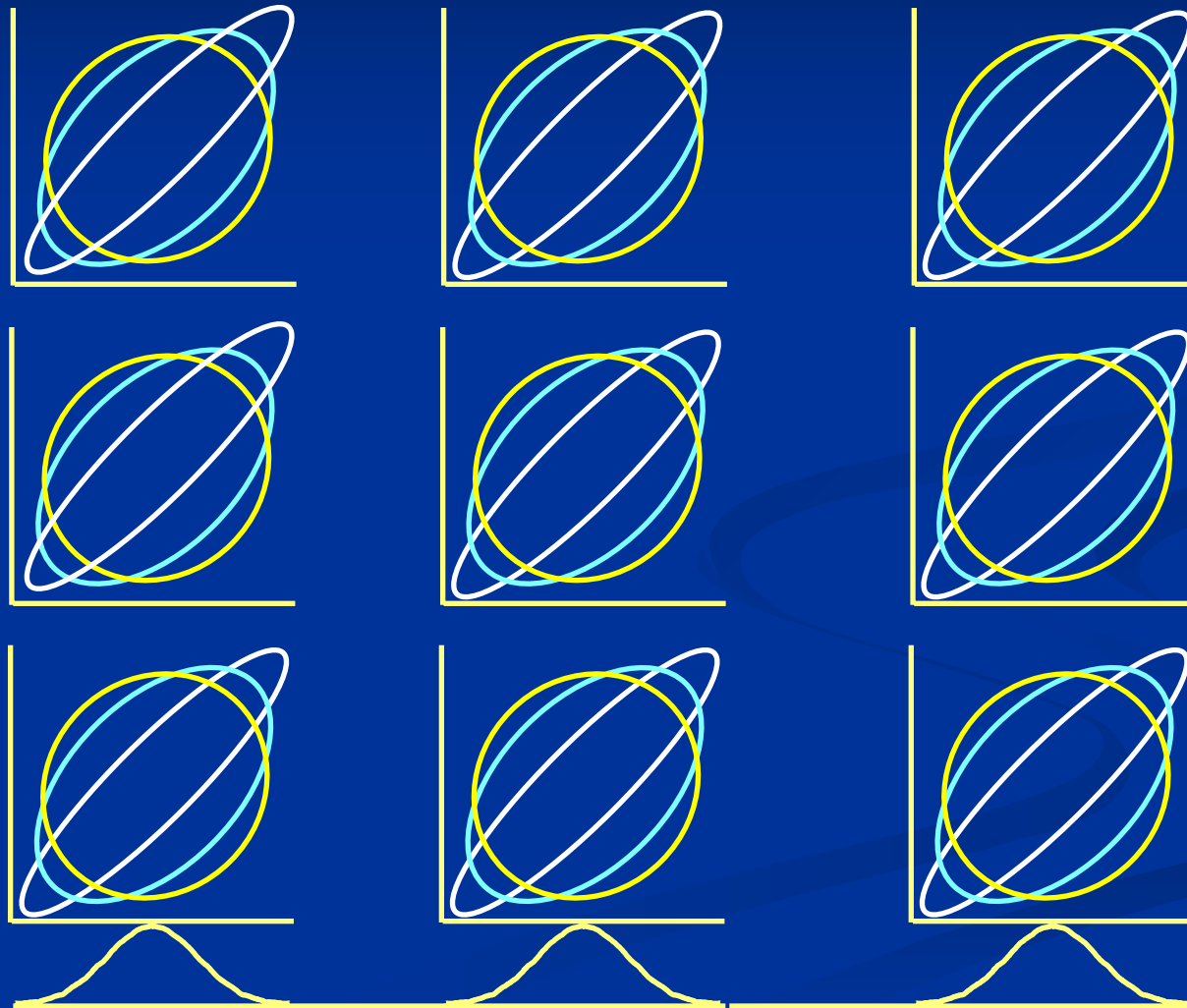
# 27 Component Mixture

Sib1

AA

Aa

aa



AA

Aa

aa

Sib 2



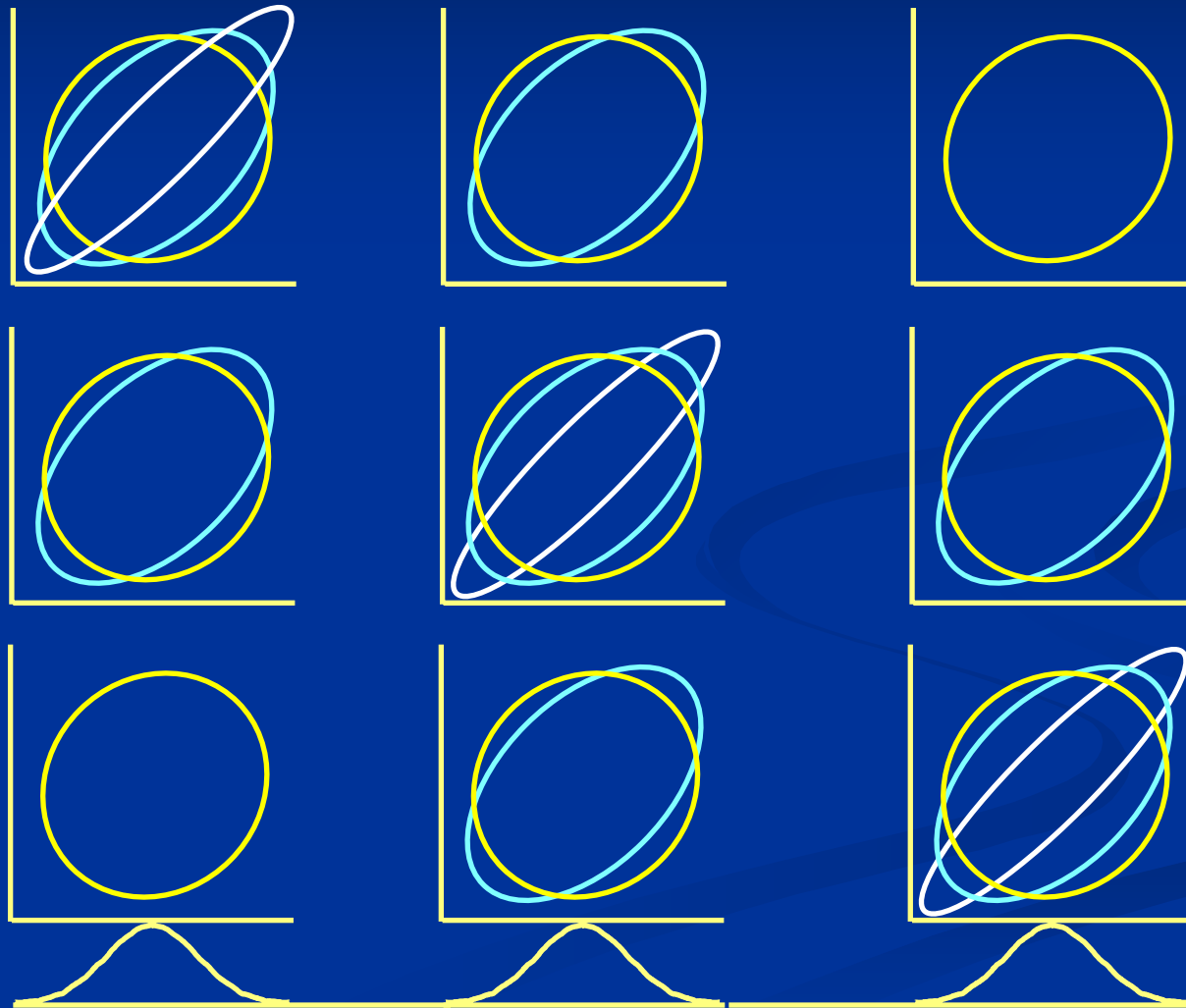
# 19 Possible Component Mixture

Sib1

AA

Aa

aa



AA

Aa

aa

Sib 2

# Results of QTL Simulation

3 Component vs 19 Component

| Parameter           | True | 3 Component | 19 Component |
|---------------------|------|-------------|--------------|
| Q                   | 0.4  | 0.414       | 0.395        |
| A                   | 0.08 | 0.02        | 0.02         |
| E                   | 0.6  | 0.56        | 0.58         |
| Test Q=0<br>(Chisq) | ---  | 13.98       | 15.88        |

200 simulations of 600 sib pairs each GASP <http://www.nhgri.nih.gov/DIR/IDRB/GASP/>

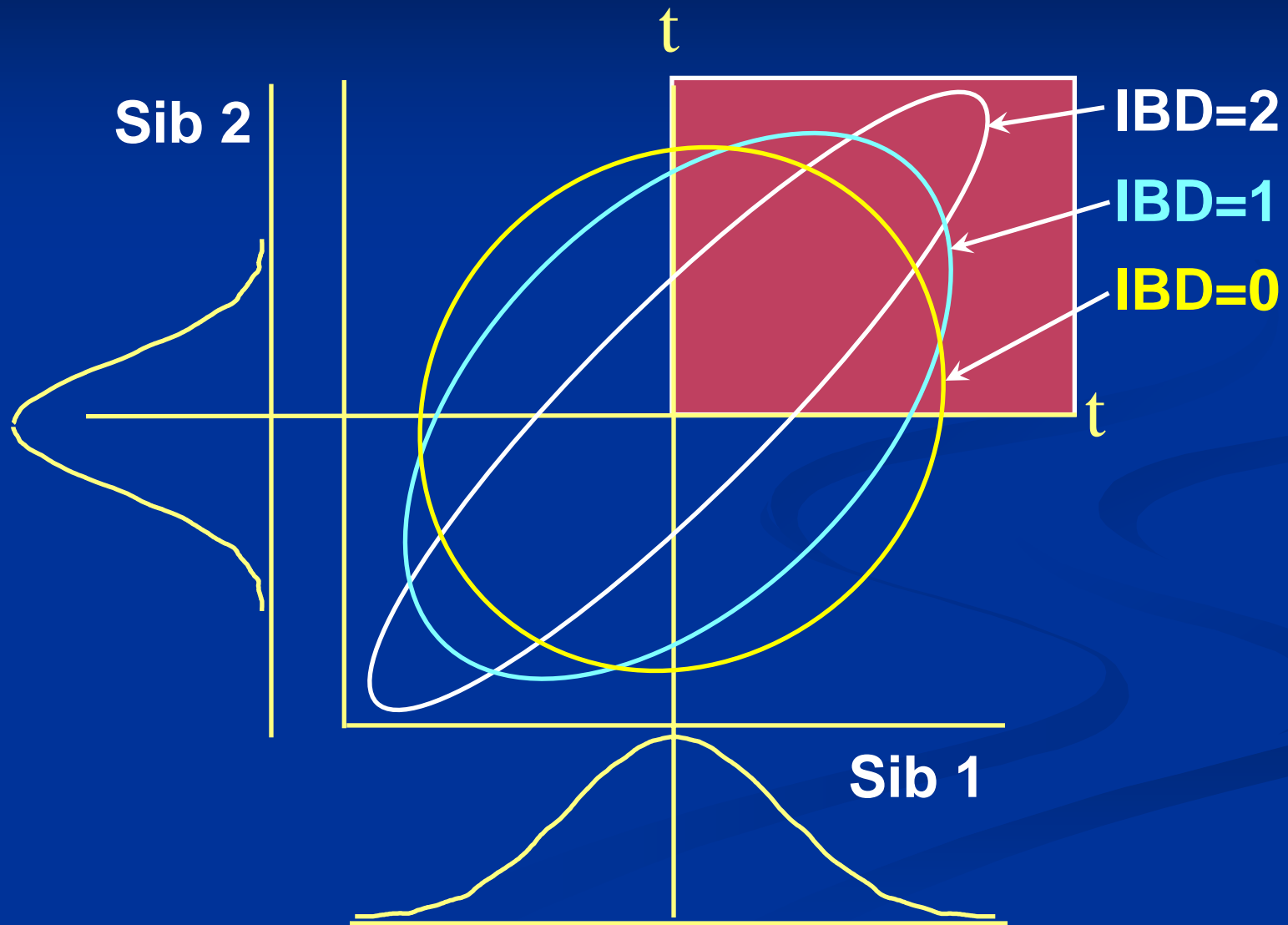
# Information in selected samples

Concordant or discordant sib pairs

- Deviation of  $\rho_{\text{hat}}$  from .5
  - Concordant high pairs  $> .5$
  - Concordant low pairs  $> .5$
  - Discordant pairs  $< .5$
- How come?

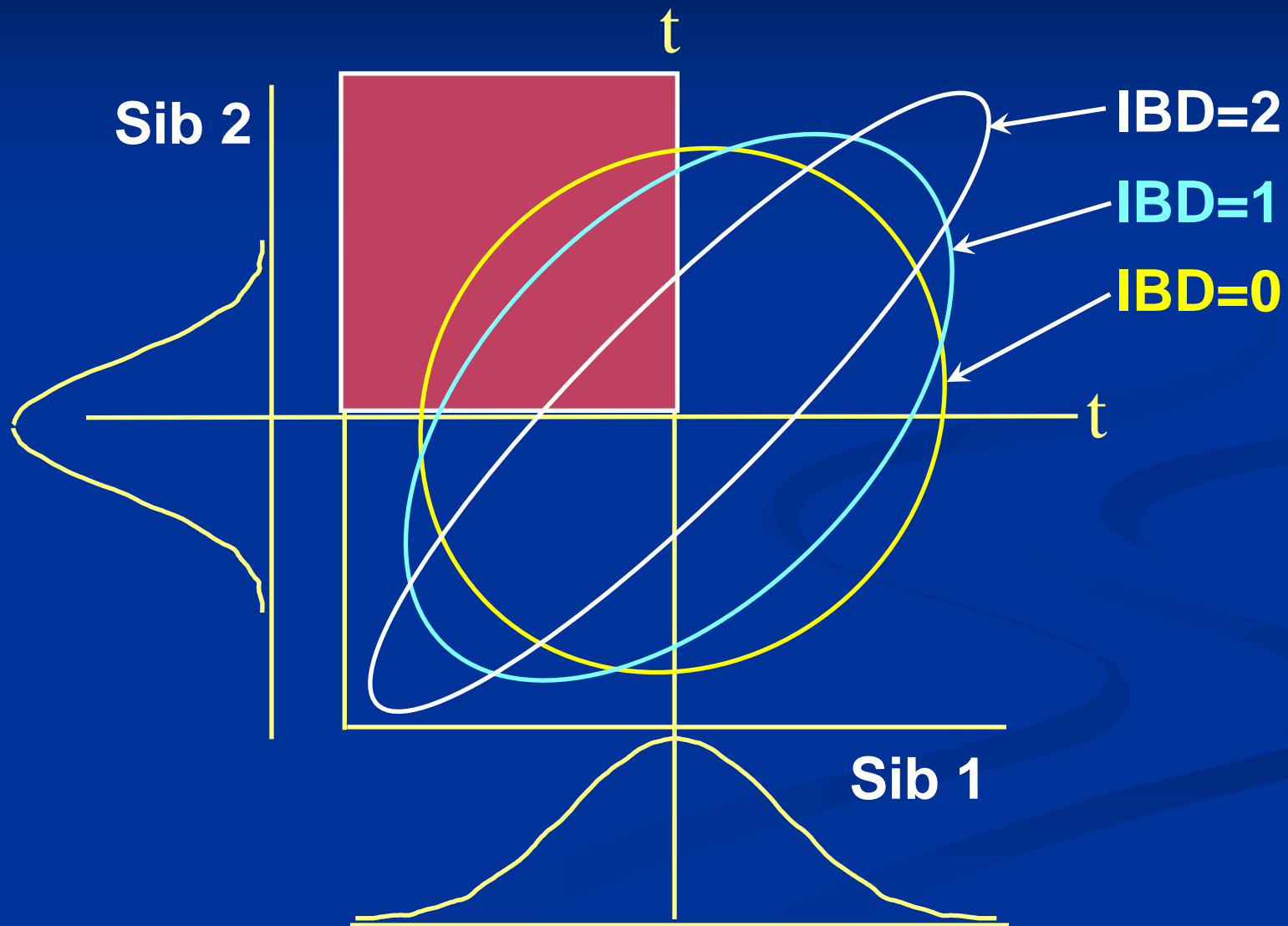
# Pihat deviates $> .5$ in ASP

Larger proportion of IBD=2 pairs

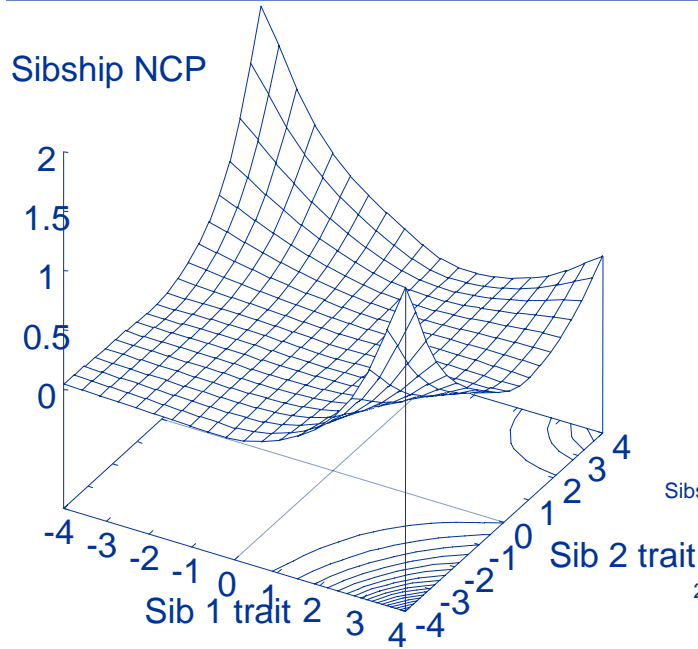


# Pihat deviates $< .5$ in DSP's

Larger proportion of IBD=0 pairs

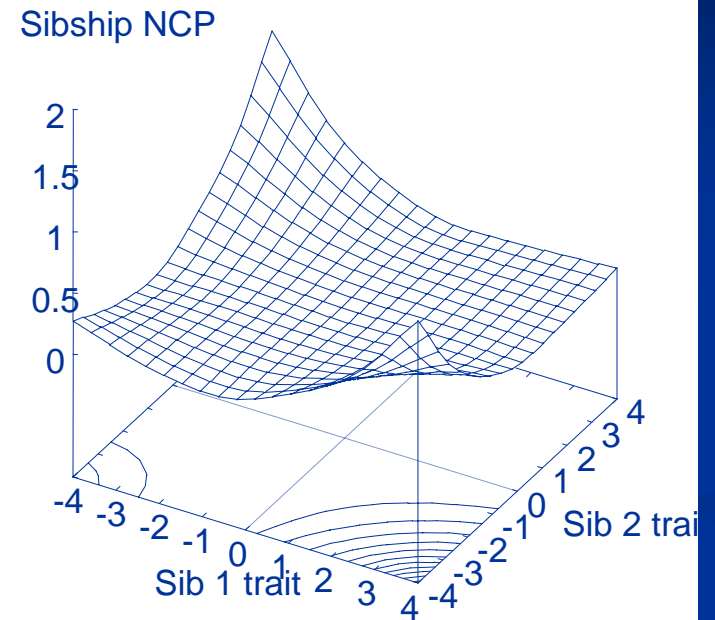
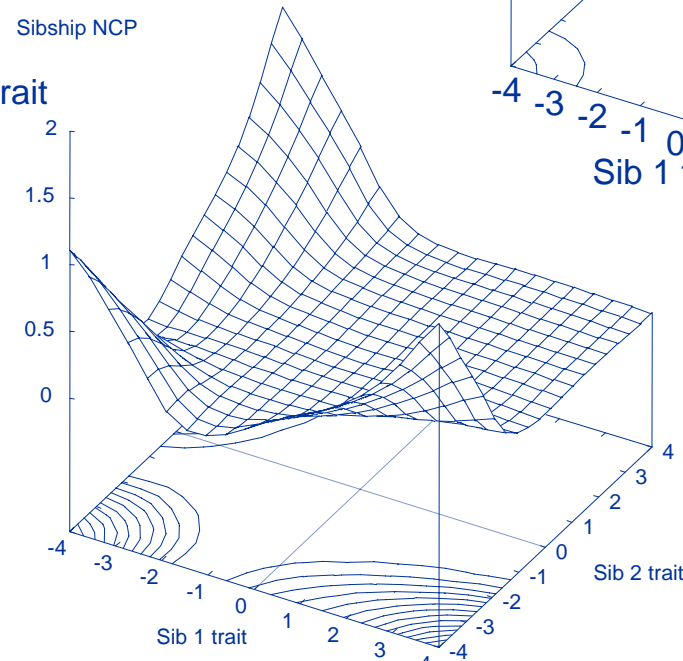


# Sibship informativeness : sib pairs



unequal allele frequencies

dominance



rare recessive

# Two sources of information

Forrest & Feingold 2000

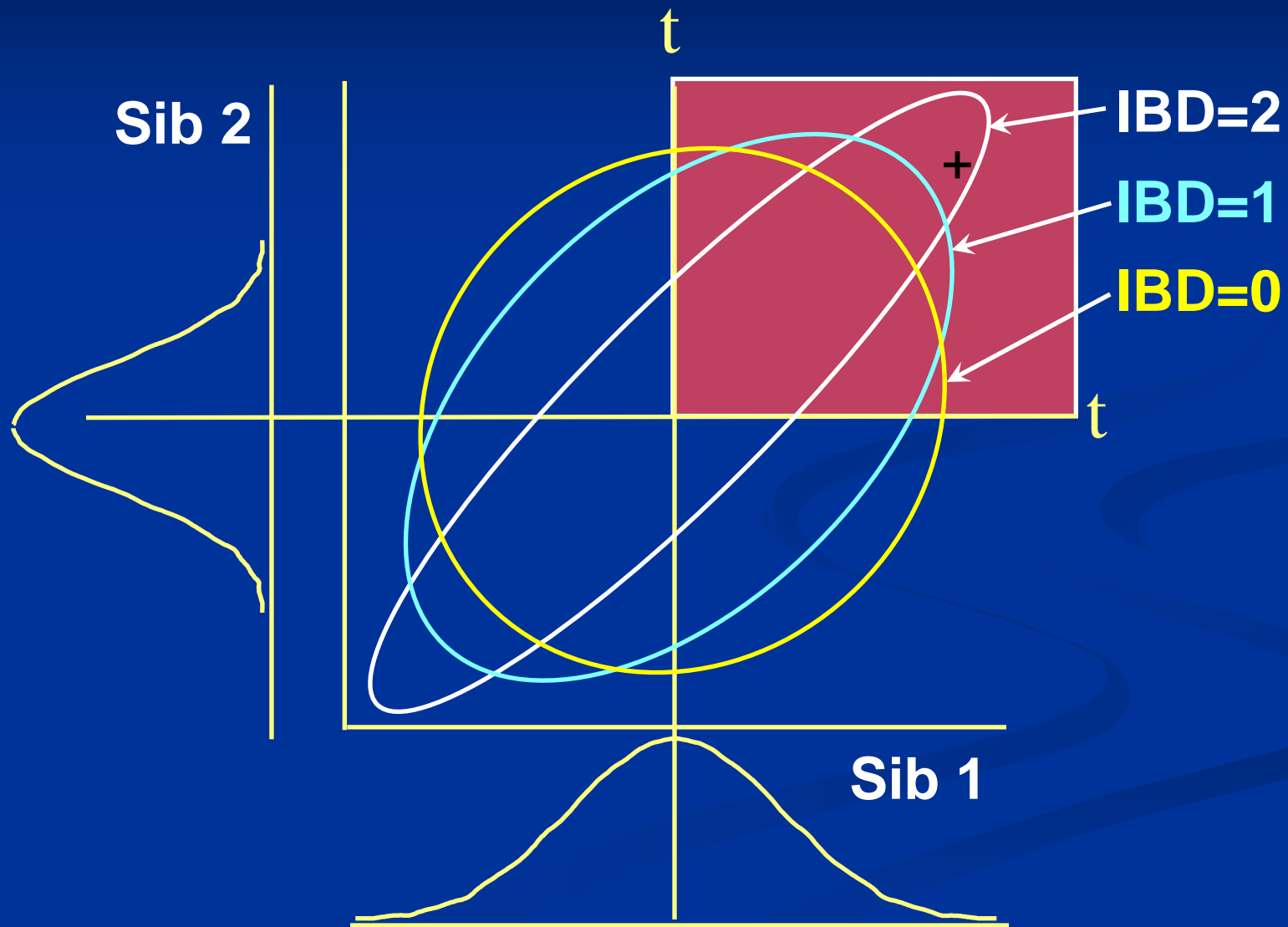
- Phenotypic similarity
  - $IBD\ 2 > IBD\ 1 > IBD\ 0$
  - Even present in selected samples
- Deviation of  $\rho_{ihat}$  from .5
  - Concordant high pairs  $> .5$
  - Concordant low pairs  $> .5$
  - Discordant pairs  $< .5$
- These sources are independent

# Implementing F&F

- Simplest form test mean  $\rho_{\text{ihat}} = .5$
- Predict amount of  $\rho_{\text{ihat}}$  deviation
  - Expected  $\rho_{\text{ihat}}$  for region of sib pair scores
  - Expected  $\rho_{\text{ihat}}$  for observed scores
- Use multiple groups in  $Mx$



# Predicting Expected Pihat deviation



# Expected Pihats: Theory

- IBD probability conditional on phenotypic scores  $X_1, X_2$

- $E(\text{pihat}) = p(\text{IBD}=2|(x_1, x_2)) + .5p(\text{IBD}=1|(x_1, x_2))$

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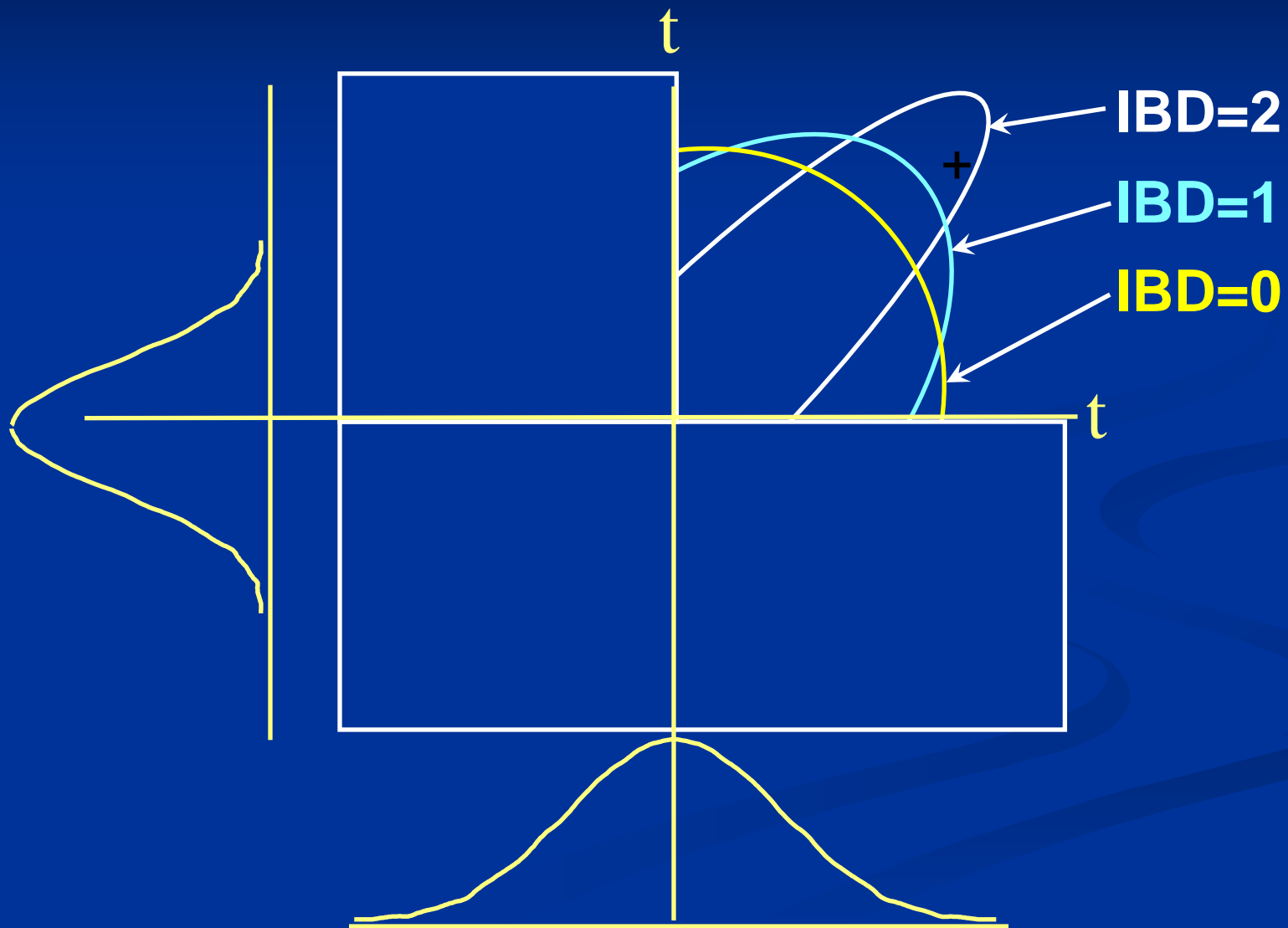
$$p(\text{IBD}=2|(x_1, x_2)) + p(\text{IBD}=1|(x_1, x_2)) + p(\text{IBD}=0|(x_1, x_2))$$

- $p(\text{IBD}=2|(x_1, x_2)) = \frac{\text{skull}_{\text{IBD}=2}(x_1, x_2)}{[\text{skull}_{\text{IBD}=2}(x_1, x_2) + 2\text{skull}_{\text{IBD}=1}(x_1, x_2) + \text{skull}_{\text{IBD}=0}(x_1, x_2)]}$

# Expected Pihats

- Compute Expected Pihats with pdfnor
- `\pdfnor(X_M_C)`
  - Observed scores  $X$  (row vector  $1 \times nvar$ )
  - Means  $M$  (row vector)
  - Covariance matrix  $C$  ( $nvar \times nvar$ )

# How to measure covariance?



# Ascertainment

- Critical to many QTL analyses
- Deliberate
  - Study design
- Accidental
  - Volunteer bias
  - Subjects dying

# Exploiting likelihood

- Correction not always necessary
  - ML MCAR/MAR
- Simulate bivariate normal data  $X, Y$
- $\Sigma = \begin{pmatrix} 1 & .5 \\ .5 & 1 \end{pmatrix}$
- $\mu = 0, 0$
- 
- 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

# Results of simulation

Population covariance  $\begin{pmatrix} 1 & .5 \\ .5 & 1 \end{pmatrix}$  Means 0, 0

| Missingness        | mean x  | mean y  | var x  | cov xy | var y  | LR Chisq |
|--------------------|---------|---------|--------|--------|--------|----------|
| MCAR (rand)<br>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)<br>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)<br>MLE | -0.0204 | 0.6805  | 0.9996 | 0.1356 | 0.2894 | 227.262  |
| sample             | 0.0448  | 0.7373  | 0.9996 |        | 0.2851 |          |

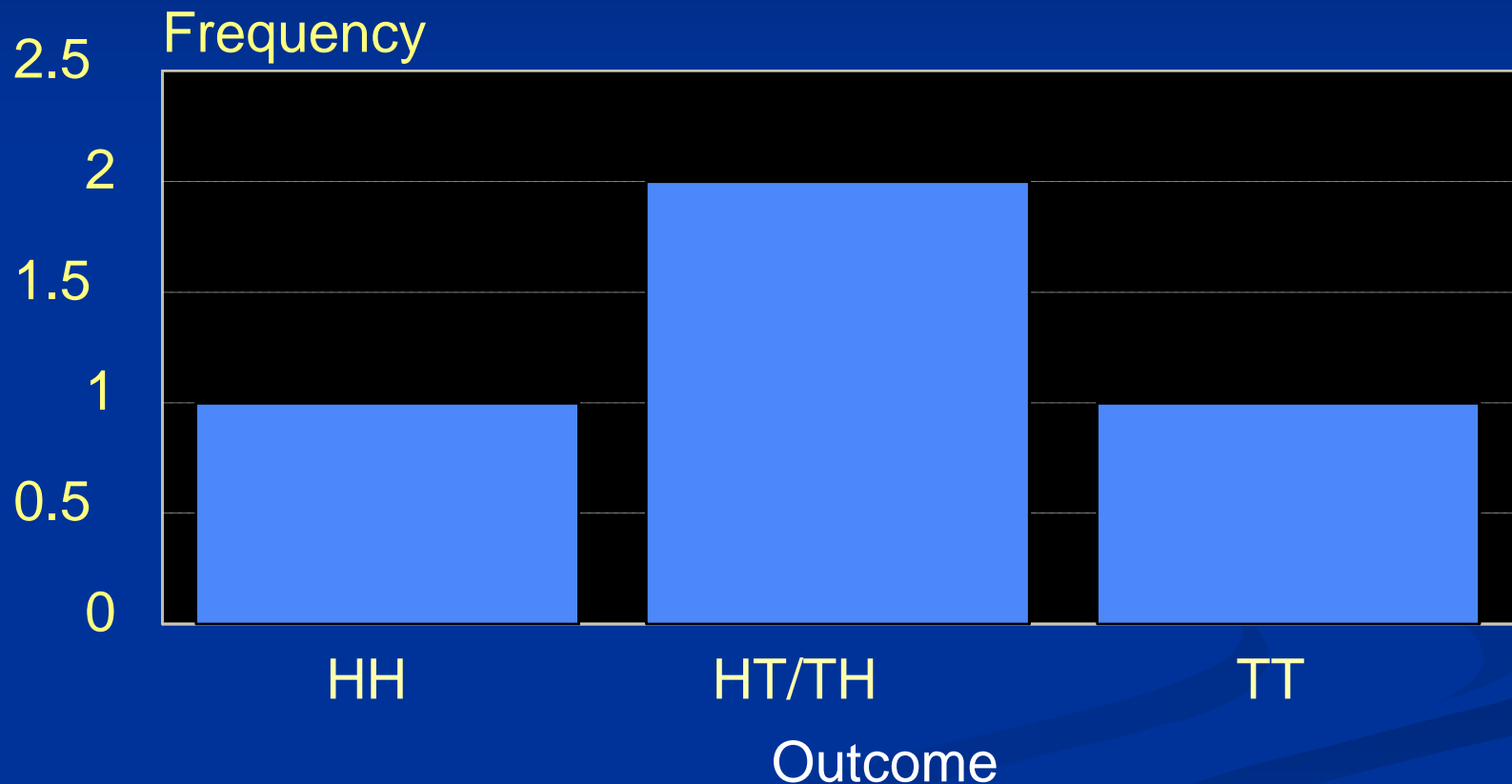
# Weighted likelihood approach

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



# Example: Two Coin Toss

3 outcomes

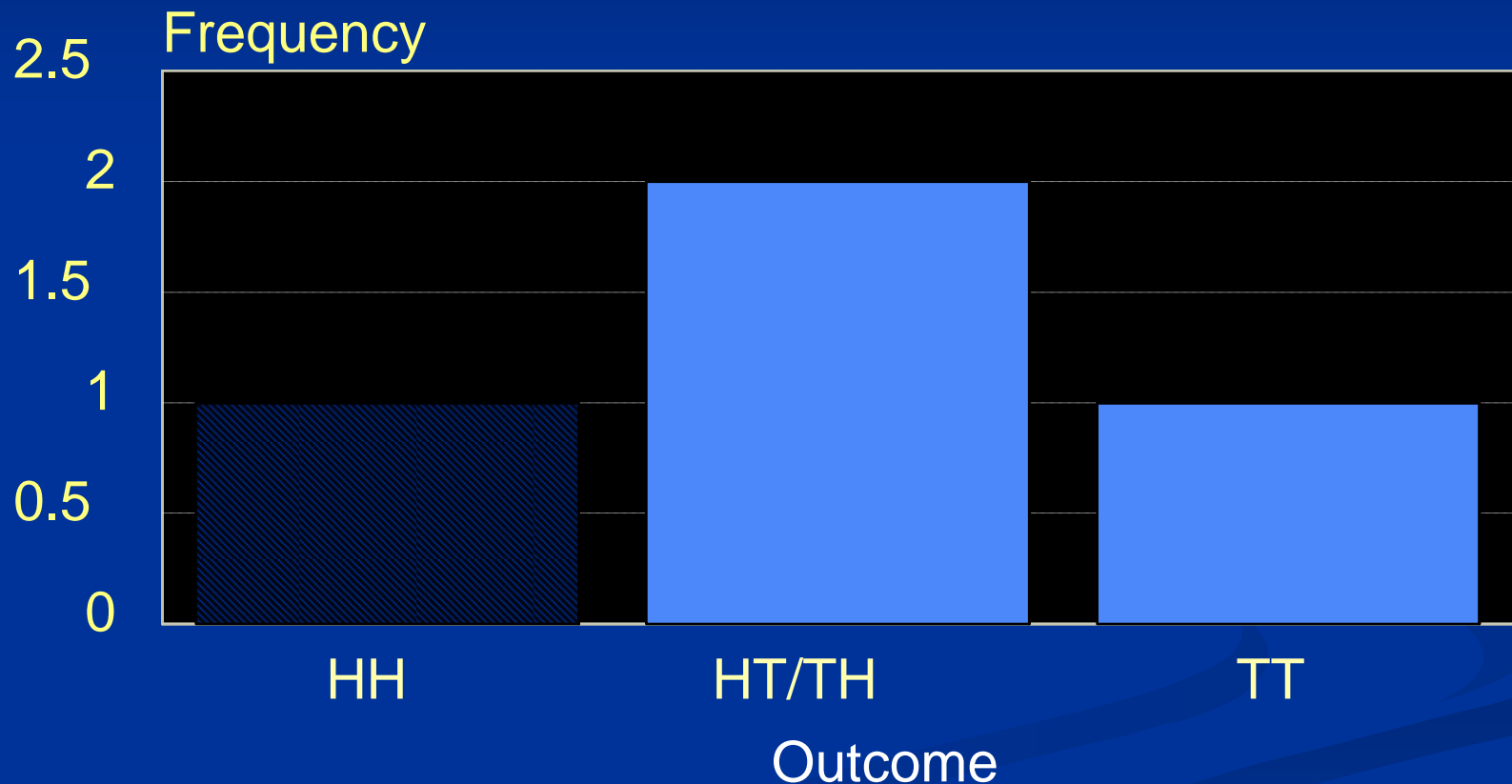


Probability  $i = \text{freq } i / \text{sum (freqs)}$

# Example: Two Coin

## Toss

3 outcomes



Probability  $i = \text{freq } i / \text{sum (freqs)}$

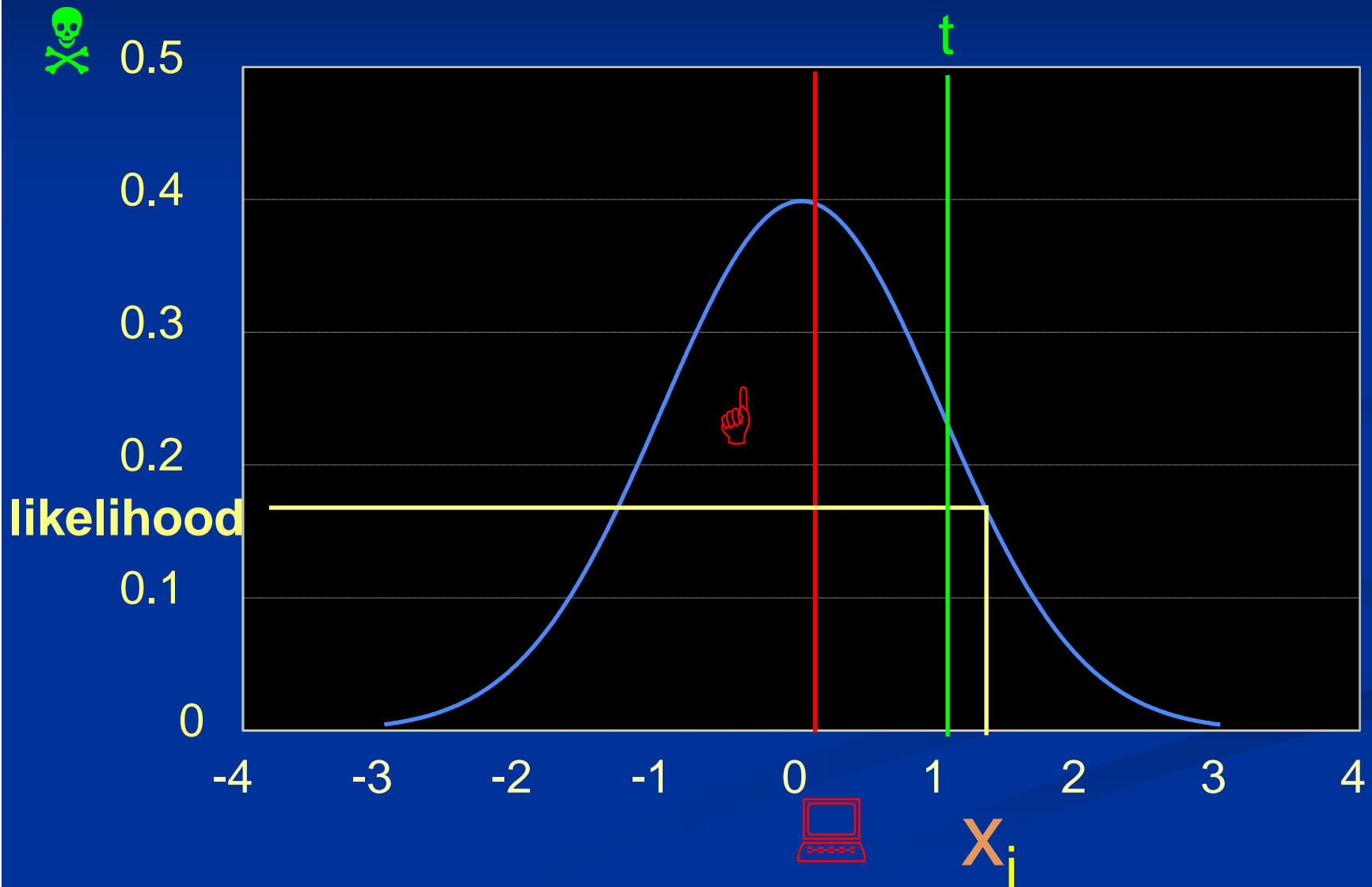
# Non-random ascertainment

Example

- Probability of observing TT globally
  - 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 case; only subjects  $> t$  ascertained



# Ascertainment Correction

- Be / All you can be

$$\text{skull and crossbones} (x)$$

---

$$\text{hand} \int \text{skull and crossbones} (x) dx$$

# Affected Sib Pairs



$t_x$

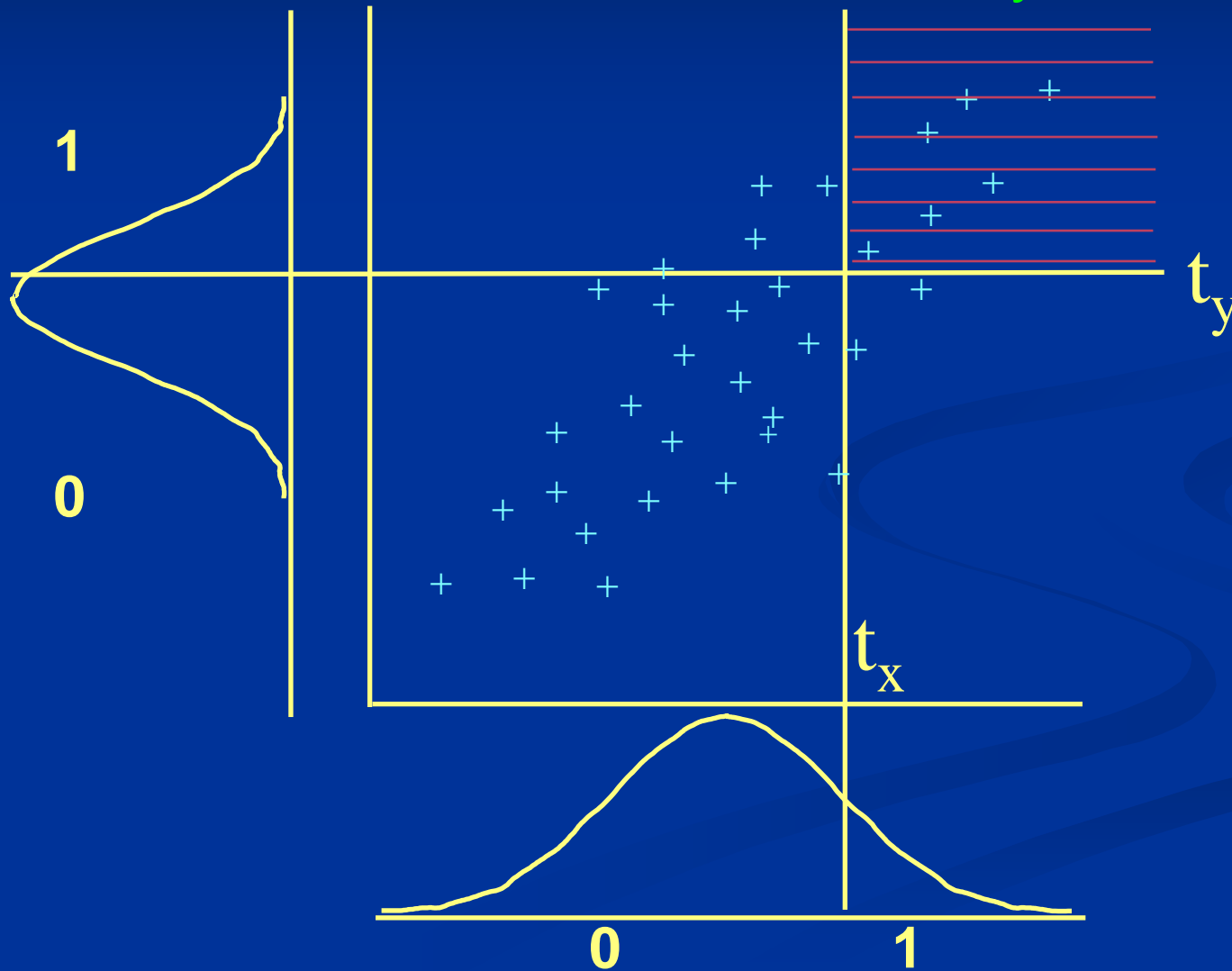


$t_y$

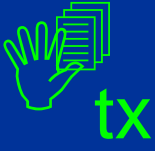
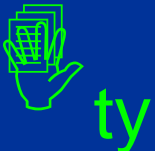



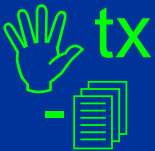
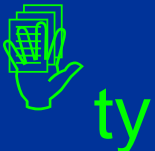

$(x,y)$

$dy$



# Ascertainment Corrections for Sib Pairs

ASP ++  tx  ty  (x,y) dy dx

DSP +-  tx  ty  (x,y) dy dx

CUSP +-  tx  ty  (x,y) dy dx

# 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



# Initial Results of Simulations

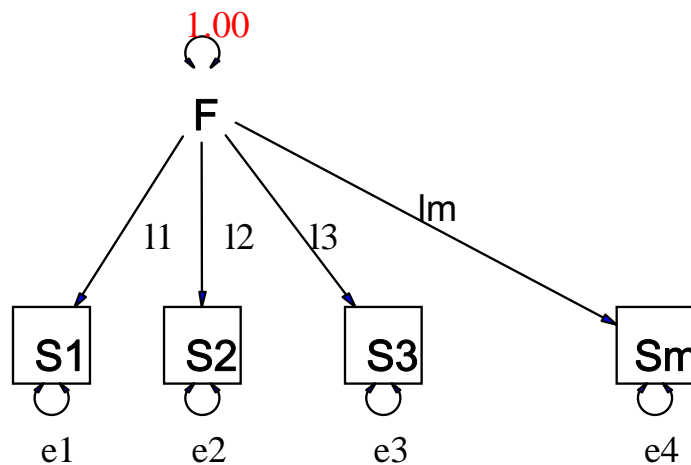
- Null Model
  - 50% heritability
  - No QTL
  - Used to generate null distribution
  - .05 empirical significance level at approximately 91 Chi-square
- QTL Simulations
  - 37.5% heritability
  - 12.5% QTL
  - Mx: 879 significant at nominal .05 p-value
  - Merlin: 556 significant at nominal .05 p-value
  - Some apparent increase in power

# Measurement is KEY

Need continuous interval scales

Most complex traits not measured this way

Use latent trait instead



Factor model equivalent to  
Item response theory model

Can allow for non-normal  
Factors

Measurement of multiple  $S_x$

# Conclusion

- Quantifying QTL variation in selected samples can be done
- Can be computationally challenging
- May provide more power
- Permits multivariate analysis of correlated traits