

# Correction for Ascertainment

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- Gemini Holdings PLC Cambridge UK

# Rationale

Why use non-random ascertainment

- Statistical Power
- IBD 2 vs IBD 0 contrast
- Increase proportion of IBD 2's: ASP
- Increase proportion of IBD 1's: DSP
- Both: EDAC

# Overview

- Rationale
- Normal Theory Maximum Likelihood
  - pros & cons
- Missing Data
- Correction for ascertainment

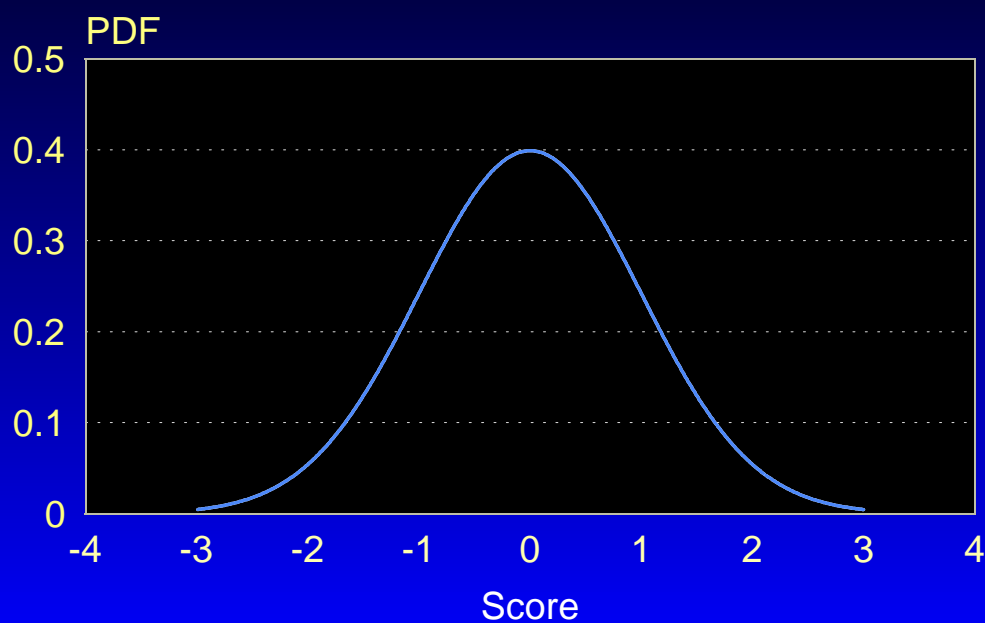
# Maximum Likelihood Estimates

Have nice properties

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

# Central Limit Theorem

Infinite factors of equal and small effect



# Normal Theory Likelihood Function

For raw data in  $M \times n$

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

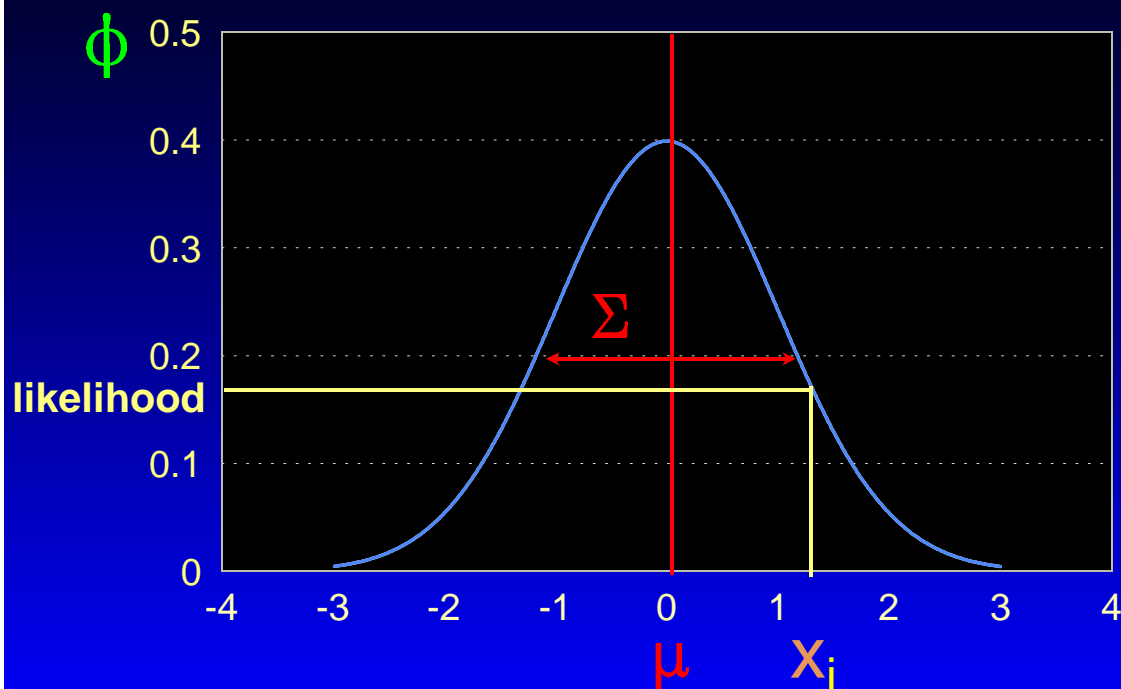
$x_i$  - vector of **observed** scores  
on  $n$  subjects

$\mu_{ij}$  - vector of predicted means

$\Sigma_{ij}$  - matrix of predicted covariances  
- functions of parameters

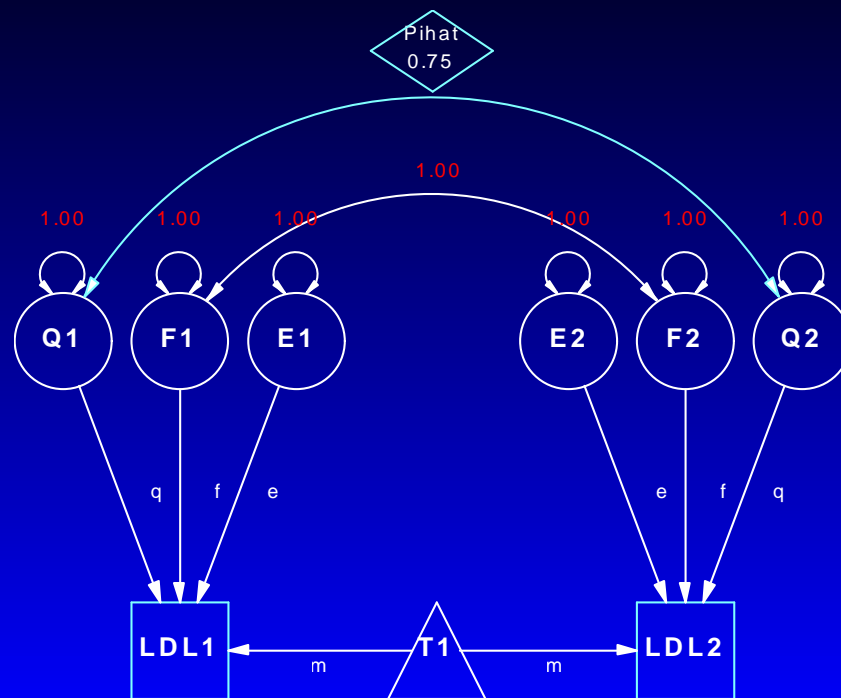
## Normal distribution $\phi(\mu_{ij}, \Sigma_{ij})$

Likelihood is height of the curve



# Pihat Linkage Model for Siblings

Each sib pair  $i$  has different COVARIANCE



## Weighted mixture of models

Finite mixture distribution

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

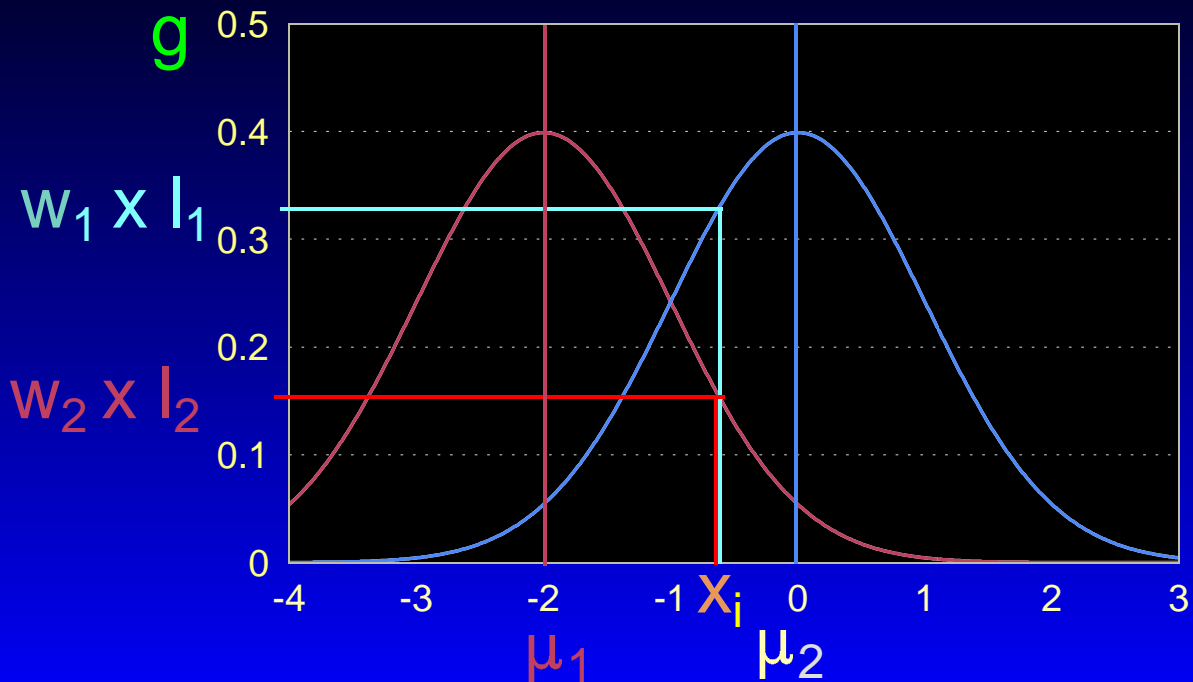
$j = 1 \dots m$  models

$w_{ij}$  Weight for subject  $i$  model  $j$

e.g., Segregation analysis

# Mixture of Normal Distributions

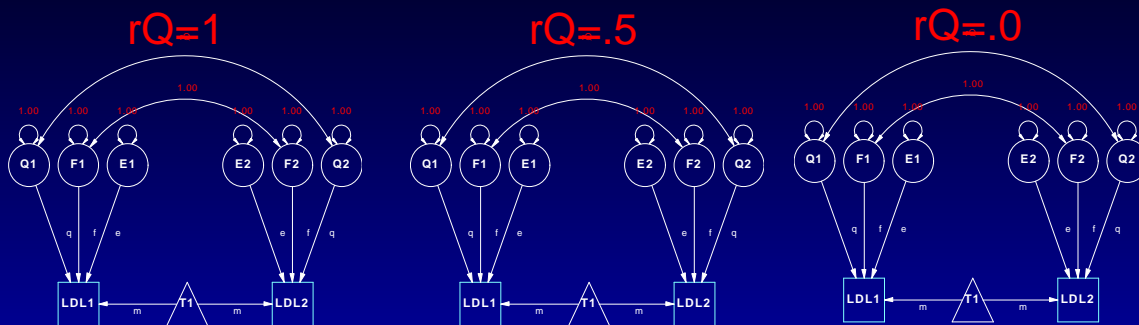
Two normals, proportions  $w_1$  &  $w_2$ , different means



But Likelihood Ratio not Chi-Squared - what is it?

# Mixture distribution model

Each sib pair  $i$  has different set of WEIGHTS



weight<sub>j</sub> x Likelihood under model j

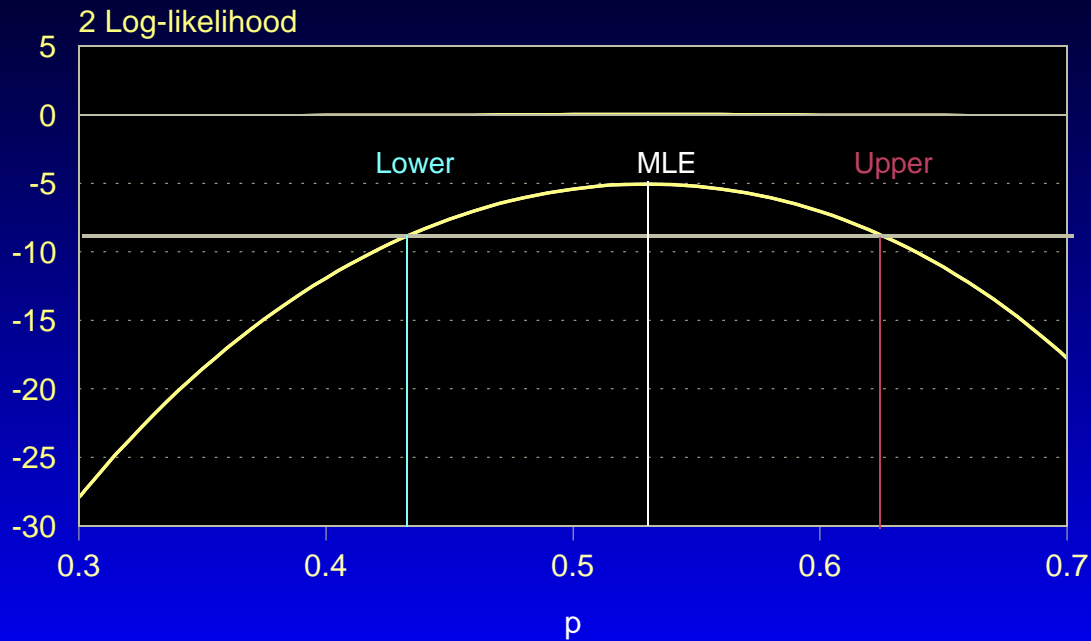
$p(\text{IBD}=2) \times P(\text{LDL1} \ \& \ \text{LDL2} \mid rQ = 1)$

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

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

Total likelihood is product of weighted likelihoods

# Likelihood-based confidence interval



3.84 units of  $2 \cdot \ln L$  give 95% confidence interval of approximately (.44; .63)

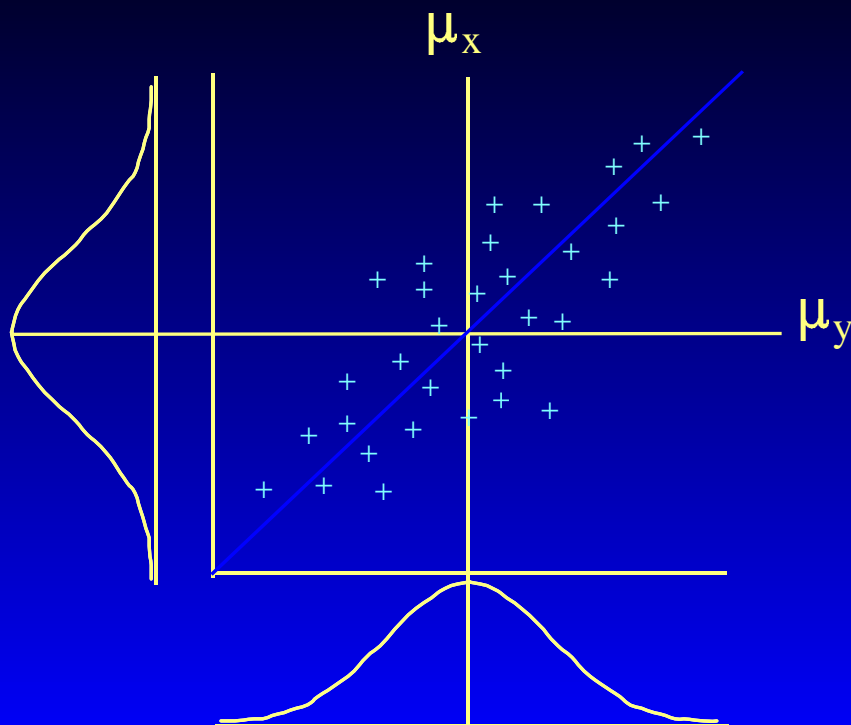
## Computing Likelihood Based Confidence Intervals

- Fix parameter in question at successive values and maximize wrt rest (grid search)
- Plot graph and interpolate (spline search)
- Redefine fit function to be e.g.
  - $(3.84 + \text{Original fit})^2 \pm \text{parameter value}$

# Outlier detection

- Continuous data case
  - Mahalanobis distance
  - Z-score
- Can do something similar for Ordinal case
- Use option `mx%p=filename` to obtain individual fit statistics

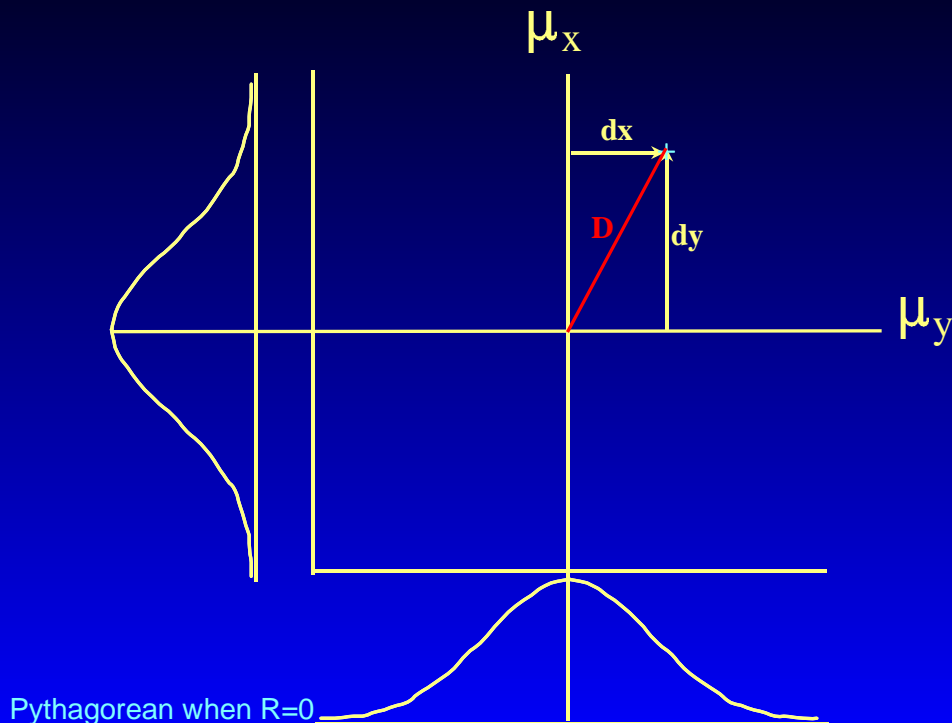
## Deviations in two dimensions





# Deviations in two dimensions

Mahalanobis distance  $D$



## Missing data

Little & Rubin 1987

- Missing completely at random
  - Causes of missingness independent
- Missing at random
  - Causes of missingness are either independent or measured
- Not missing at random
  - Due to residual variance in the missing variable itself

# Computing likelihood

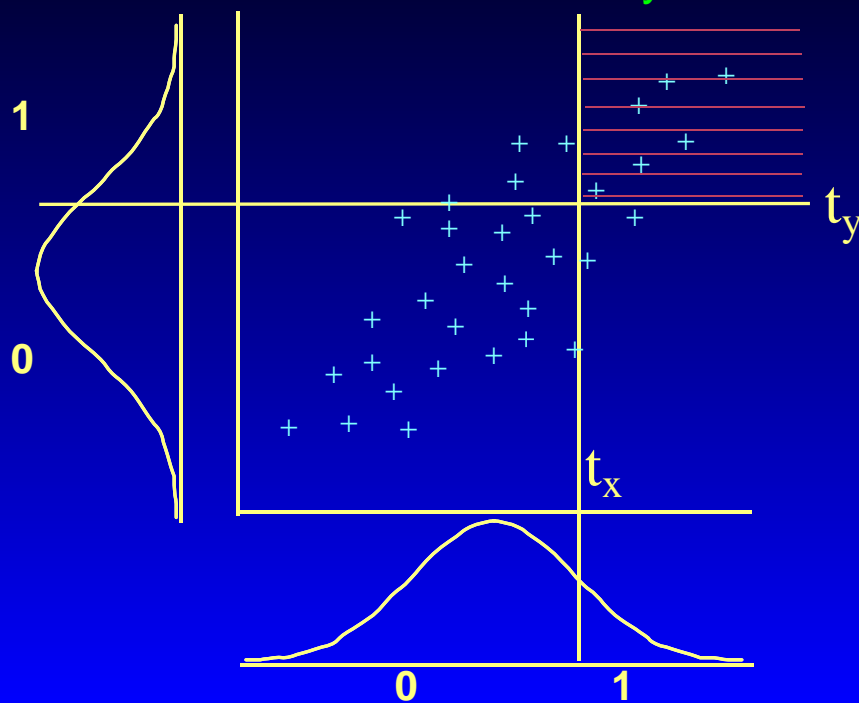
In presence of missing data

- Formally
  - Integrate over all missing value could be

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

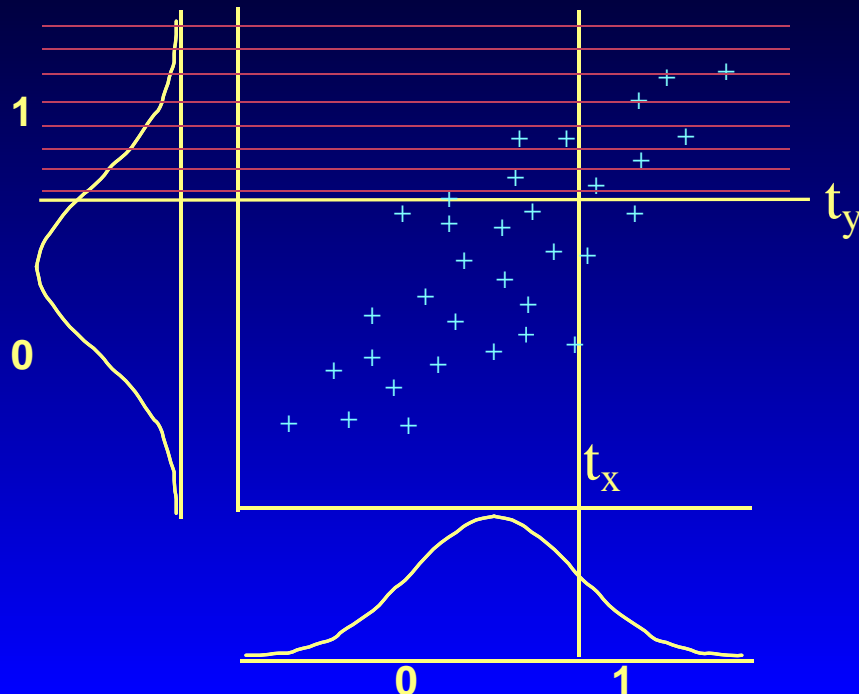
**Data  $X = 1$   $Y = 1$**

$$\int_{t_x}^\infty \int_{t_y}^\infty \phi(x,y) dy dx$$



**Data  $X = 1$   $Y = .$**

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



## In practice

What Mx does

- Continuous case
  - Filter covariance and mean/threshold matrix and pretend
- Ordinal case
  - Filter threshold and covariance matrix and compute easier integral

# Linkage analysis

- Analyze genotyped pairs and non-genotyped pairs together
- Assign prior probabilities for IBD for non-genotyped pairs
- Look out for bias

## Approach 2

Correcting for Ascertainment

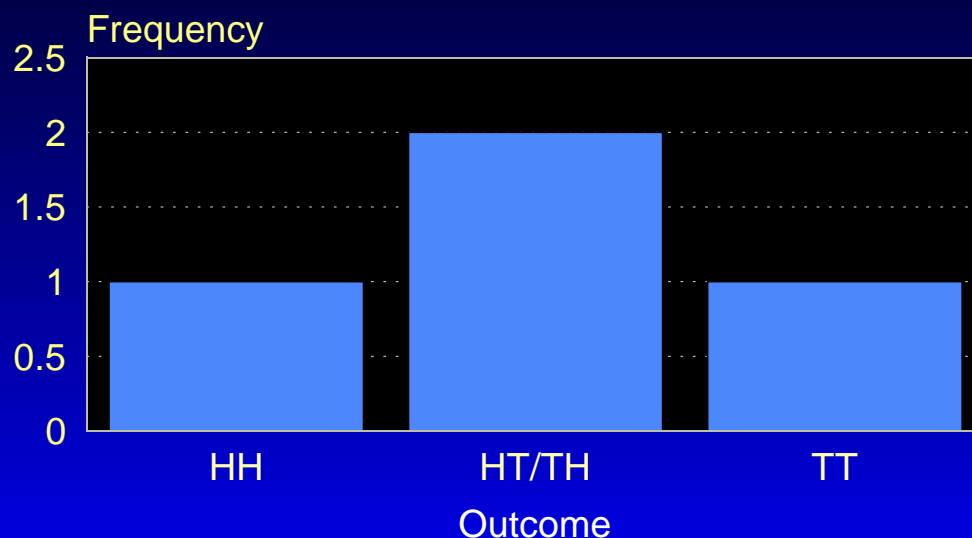
- Use only genotyped pairs
- Unscrew likelihood (why?)

# Ascertainment Examples

- Studies of patients and controls
- Patients and relatives
- Linkage studies
  - Affected sib pairs, DSP etc
  - Multiple affected families

## Example: Two Coin Toss

3 outcomes



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

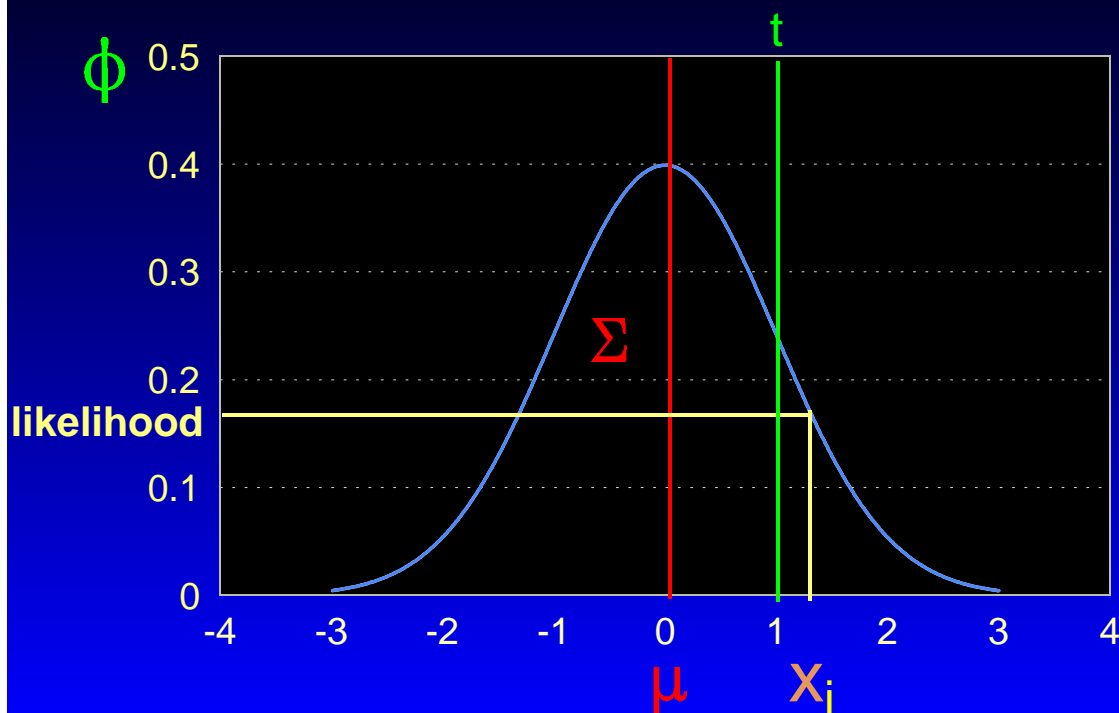
# Non-random ascertainment

## 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  $3/4$  =  $1/3$

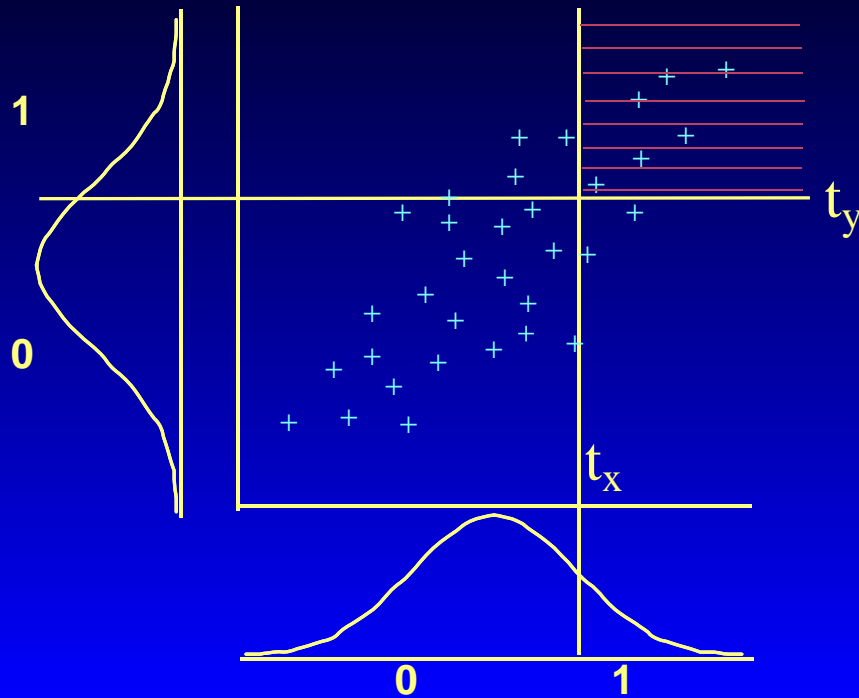
# Correcting for ascertainment

Univariate case; only subjects  $> t$  ascertained



## Affected Sib Pairs

$$\int_{t_x}^{\infty} \int_{t_y}^{\infty} \phi(x,y) dy dx$$



## 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:

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

- With ascertainment, the correction is

$$\int_t^{\infty} \phi(\mu_{ij}, \Sigma_{ij}) dx$$

## Correcting for ascertainment

- 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

## Pihat vs Mixture

Ascertainment

- Mixture: 3 models, invariant over subjects
  - 3 ascertainment corrections
  - Modify Weights
- Pihat: N sibs different covariance models
  - Compute ascertainment correction for each sib pair



# General Likelihood Function

What about the means  $\mu_{ij}$ ?

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

Have varied  $\Sigma_{ij}$  (pihat) or  $w_{ij}$  (full IBD)

Association analysis varies  $\mu_{ij}$   
causes trouble for asc correction

## Correction for ascertainment

Joint linkage and association analysis

- Better watch out
- Correction  $w_j$  depends on
  - predicted means  $\mu_{ij}$  (9 types)
  - predicted covariances,  $\Sigma_{ij}$  (3 types)
  - could still pre-compute 27 integrals & pick
- Careful if you are modeling covariates like age via means

# Two sources of information

In selected samples

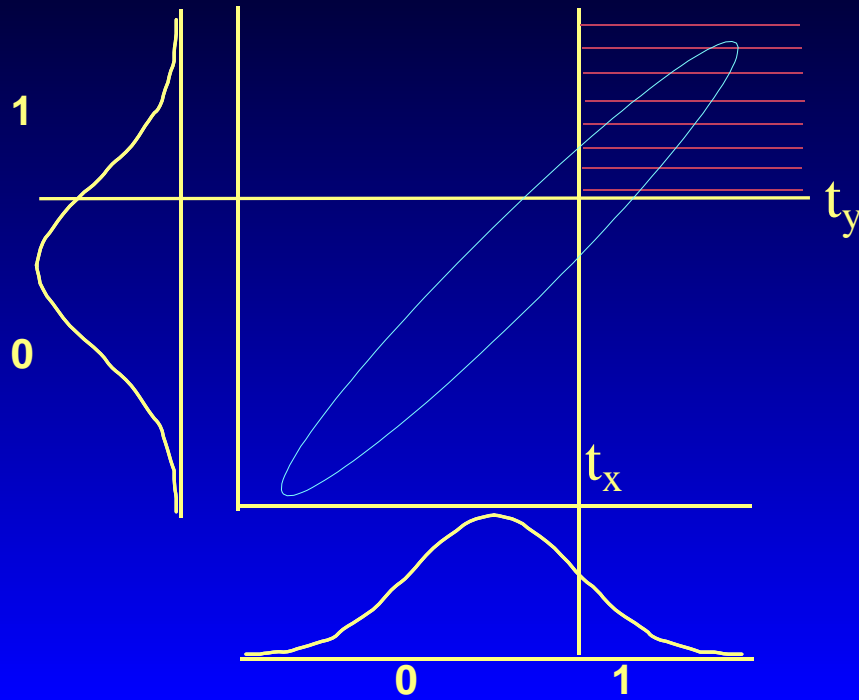
- Difference in covariance as a function of IBD status
- Deviation of average  $\hat{p}$  from .5
- Use them both?
  - Read in  $\hat{p}$  in a separate group
  - Estimate mean & variance
  - Set mean to .5

# Expected $\hat{p}$ Approach

- For a given  $q^2$  can we predict what  $\hat{p}$  should be under selection?
- Three distributions, initially .25 .5 .25
- Compute three integrals
  - recompute proportions

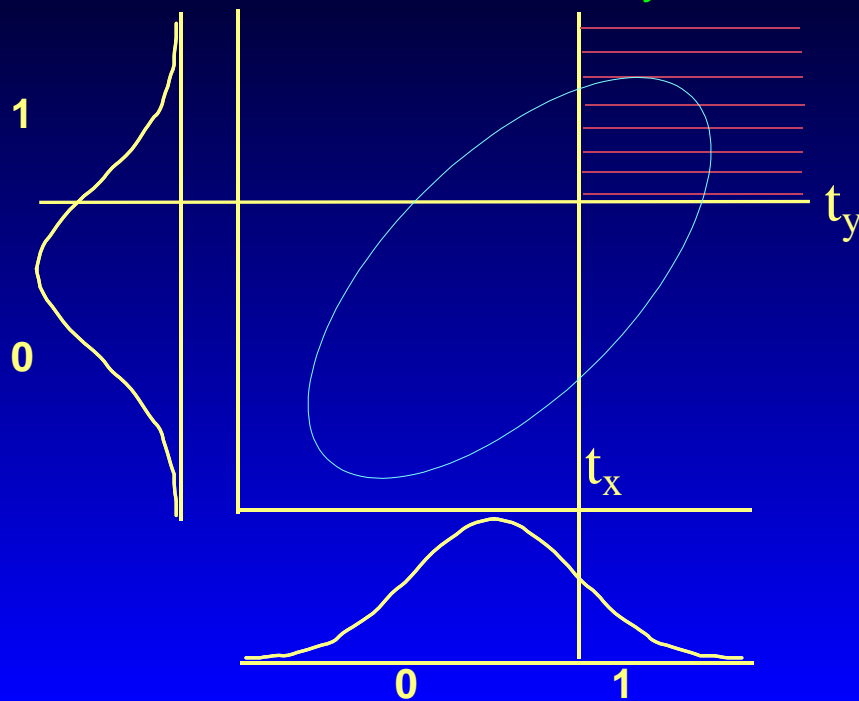
## High correlation (IBD 2)

$$\int_{t_x}^{\infty} \int_{t_y}^{\infty} \phi(x,y) dy dx$$



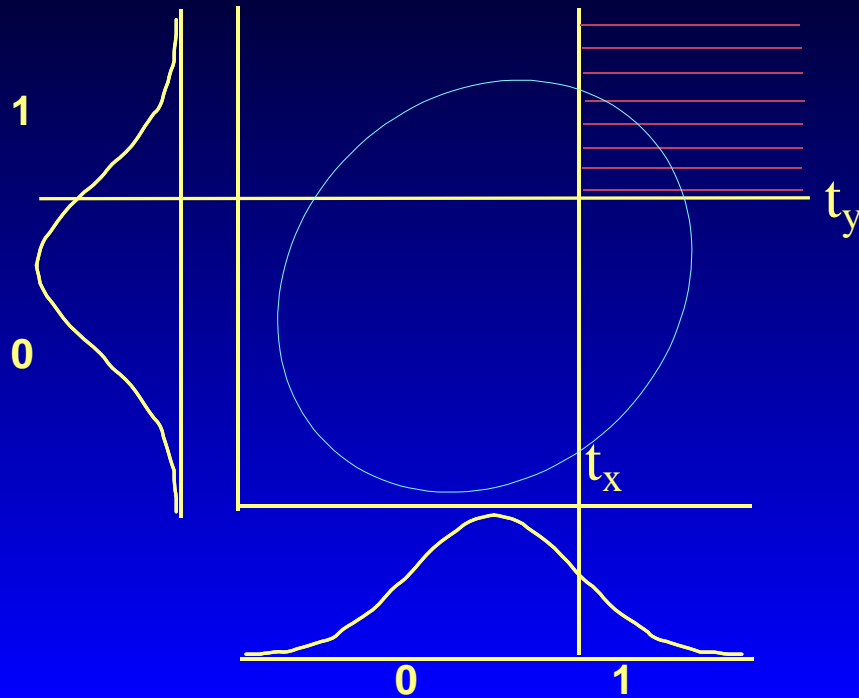
## Medium correlation (IBD 1)

$$\int_{t_x}^{\infty} \int_{t_y}^{\infty} \phi(x,y) dy dx$$



## Low correlation (IBD 0)

$$\int_{t_x}^{\infty} \int_{t_y}^{\infty} \phi(x,y) dy dx$$



## Conclusion

- Can handle non-random ascertainment in two ways
- Include screened but not genotyped pairs in analysis
- Use only genotyped pairs
- Make use of 'marginal' average pi-hat info