

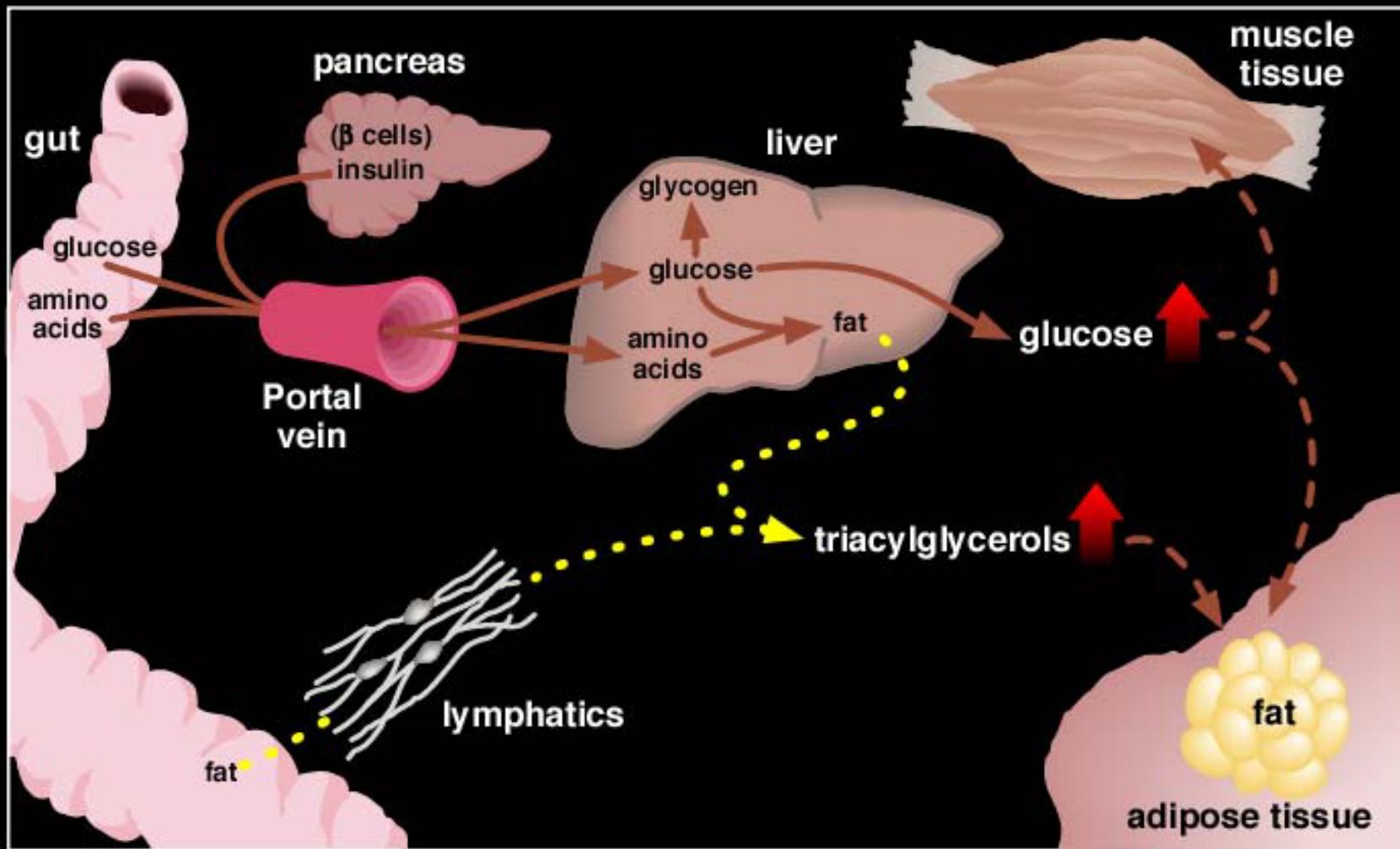
Multiple Traits & Microarrays

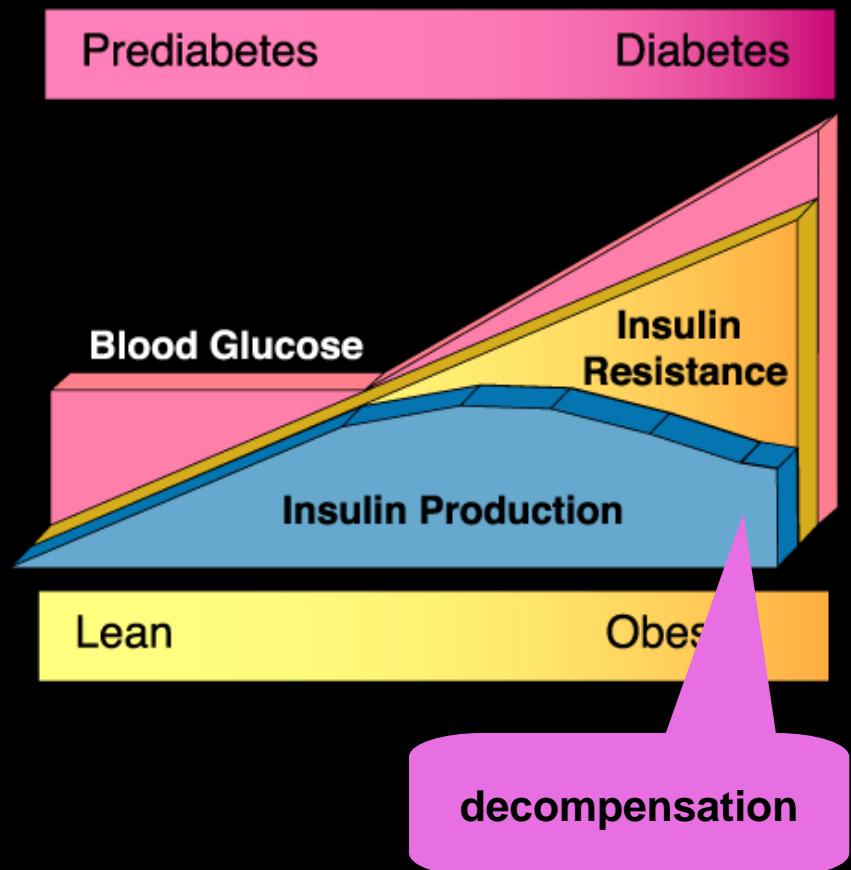
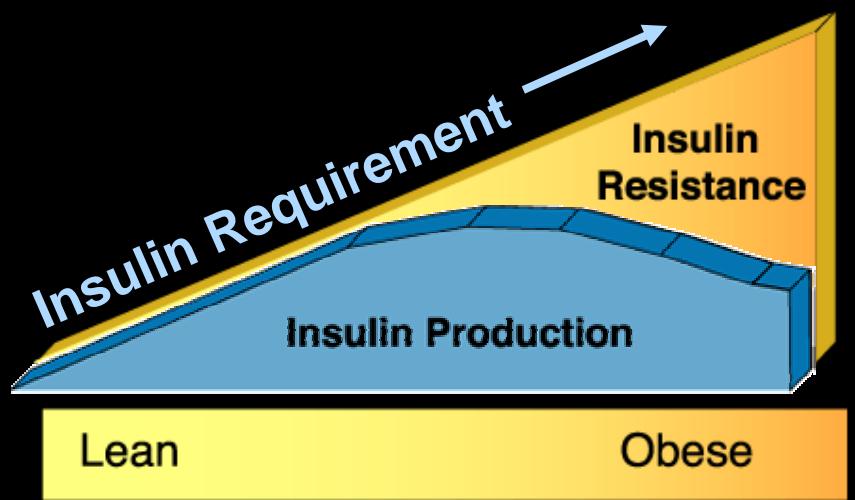
- | | |
|---|-------|
| 1. why study multiple traits together? | 2-13 |
| – diabetes case study | |
| – central dogma via microarrays | |
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| – close linkage or pleiotropy? | |
| 4. how to handle high throughput? | 27-40 |
| – dimension reduction: multivariate stats | |
| – principal components on phenotypes | |

1. why study multiple traits together?

- avoid reductionist approach to biology
 - address physiological/biochemical mechanisms
 - Schmalhausen (1942); Falconer (1952)
- separate close linkage from pleiotropy
 - 1 locus or 2 linked loci?
- identify epistatic interaction or canalization
 - influence of genetic background
- establish QTL x environment interactions
- decompose genetic correlation among traits
- increase power to detect QTL

Type 2 Diabetes Mellitus





from Unger & Orci *FASEB J.* (2001) 15,312

Insulin Resistant Mice



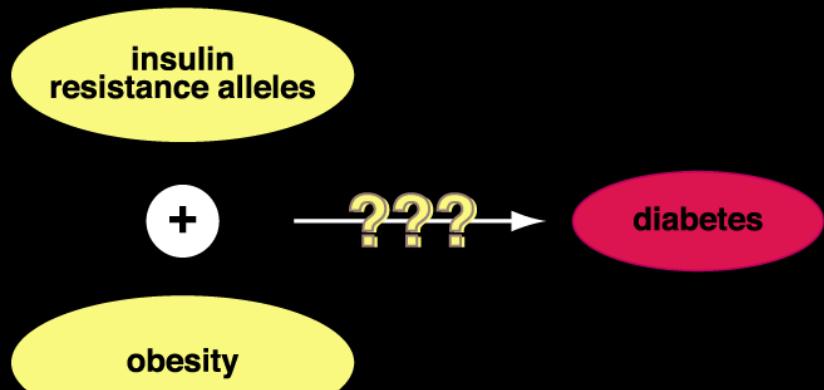
Bill Dove



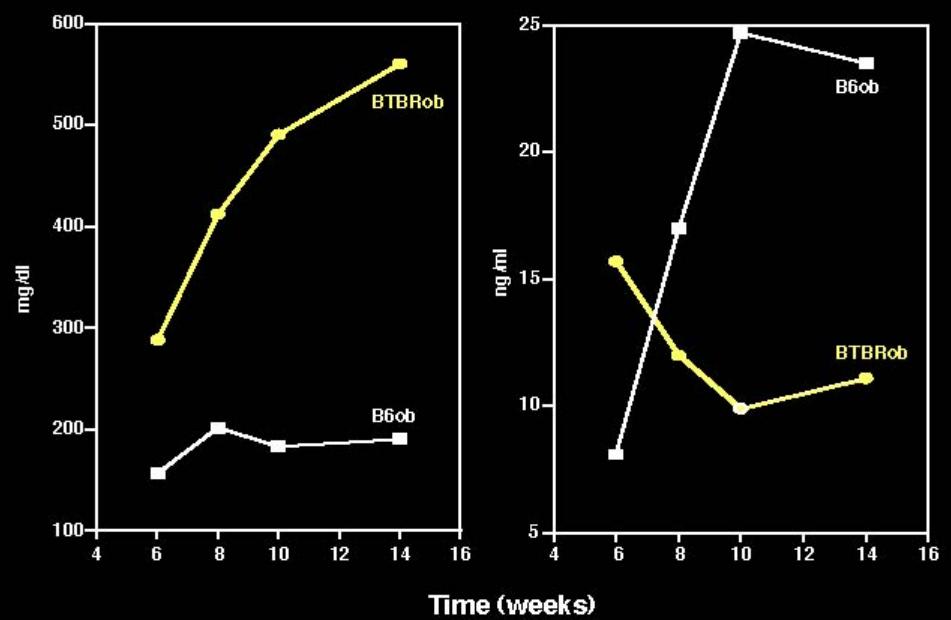
BTBR strain

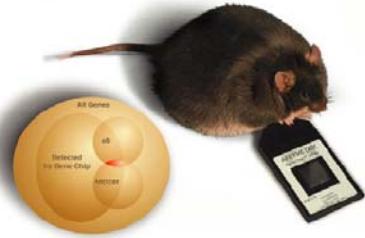


glucose insulin



(courtesy AD Attie)





studying diabetes in an F2

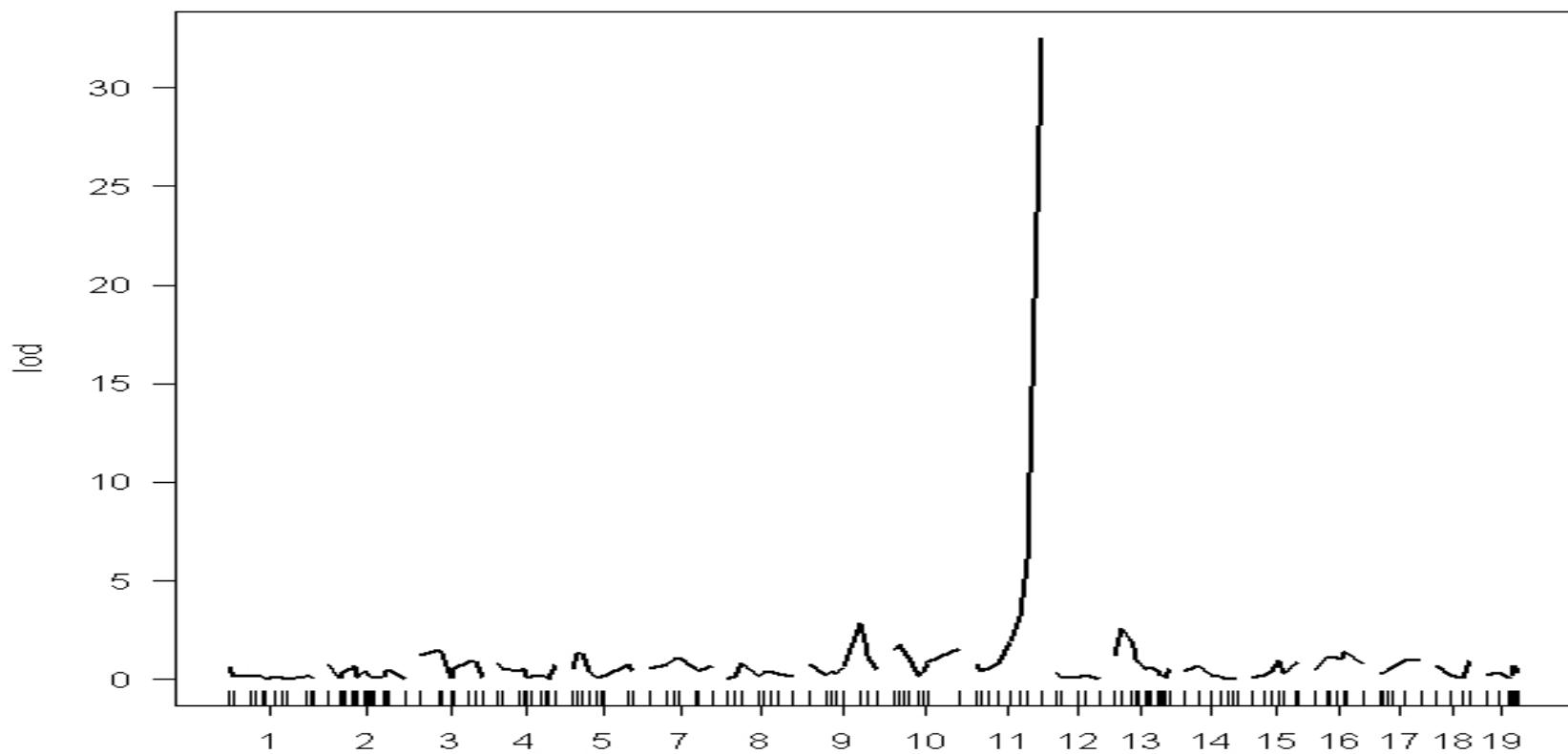
- segregating cross of inbred lines
 - B6.ob x BTBR.ob → F1 → F2
 - selected mice with ob/ob alleles at leptin gene (chr 6)
 - measured and mapped body weight, insulin, glucose at various ages (Stoehr et al. 2000 *Diabetes*)
 - sacrificed at 14 weeks, tissues preserved
- gene expression data
 - Affymetrix microarrays on parental strains, F1
 - (Nadler et al. 2000 *PNAS*; Ntambi et al. 2002 *PNAS*)
 - RT-PCR for a few mRNA on 108 F2 mice liver tissues
 - (Lan et al. 2003 *Diabetes*; Lan et al. 2003 *Genetics*)
 - Affymetrix microarrays on 60 F2 mice liver tissues
 - design (Jin et al. 2004 *Genetics* tent. accept)
 - analysis (work in prep.)

why map gene expression as a quantitative trait?

- *cis-* or *trans*-action?
 - does gene control its own expression?
 - or is it influenced by one or more other genomic regions?
 - evidence for both modes (Brem et al. 2002 Science)
- simultaneously measure all mRNA in a tissue
 - ~5,000 mRNA active per cell on average
 - ~30,000 genes in genome
 - use genetic recombination as natural experiment
- mechanics of gene expression mapping
 - measure gene expression in intercross (F2) population
 - map expression as quantitative trait (QTL)
 - adjust for multiple testing



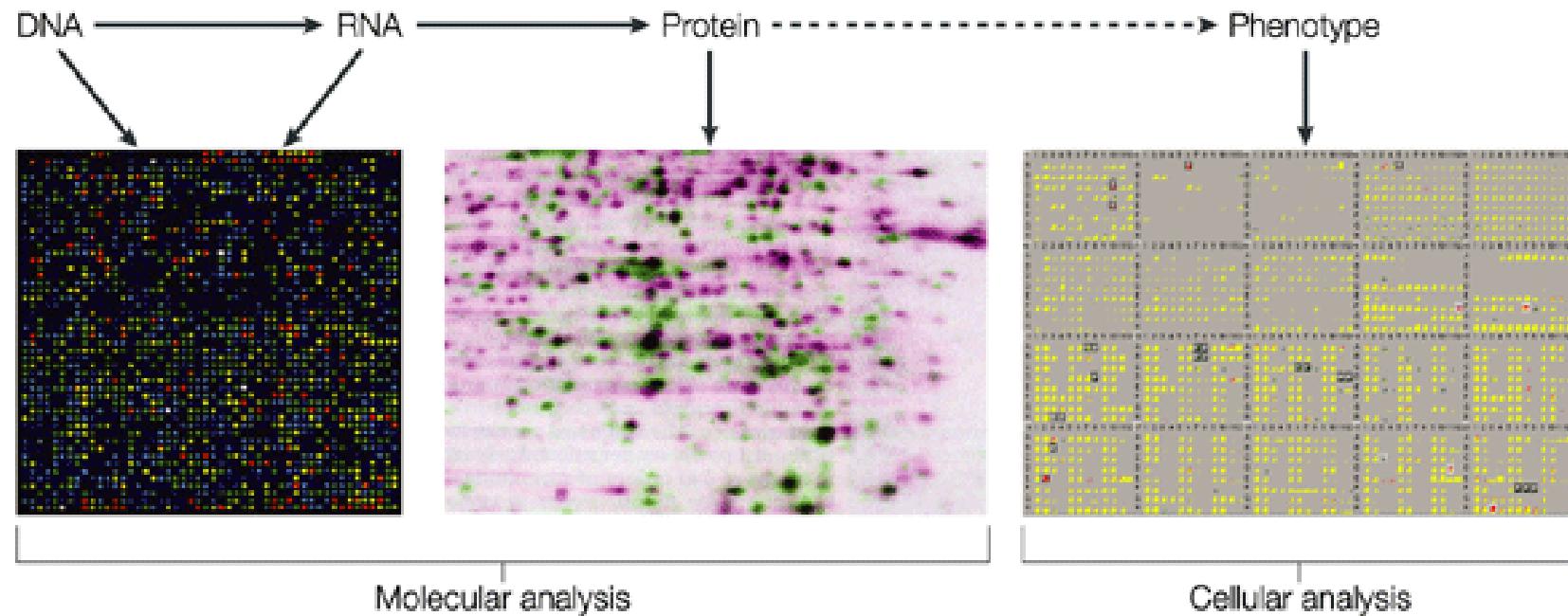
LOD map for PDI: *cis*-regulation (Lan et al. 2003)



mapping microarray data

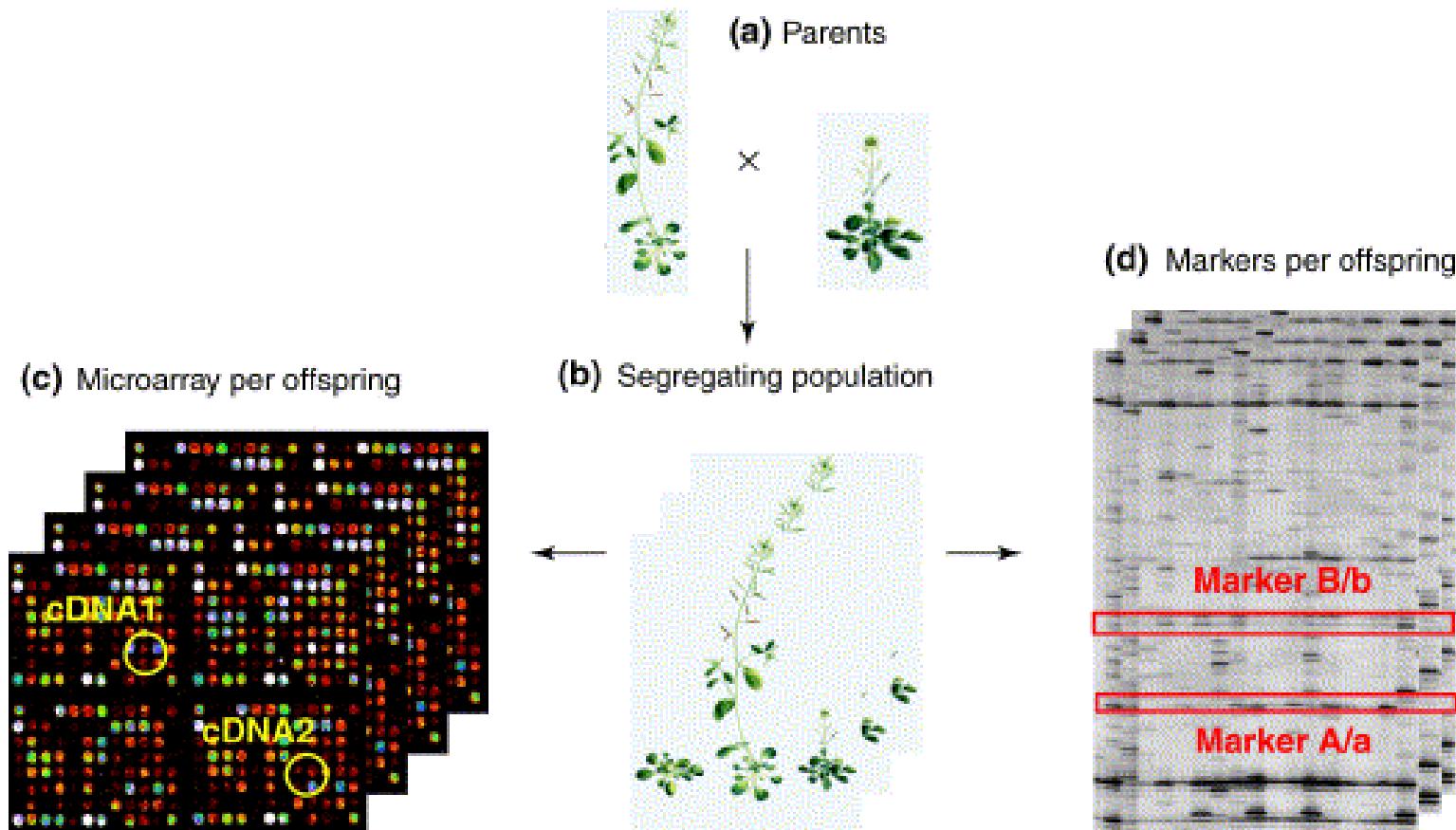
- single gene expression as trait (single QTL)
 - Dumas et al. (2000 *J Hypertens*)
- overview, wish lists
 - Jansen, Nap (2001 *Trends Gen*); Cheung, Spielman (2002); Doerge (2002 *Nat Rev Gen*); Bochner (2003 *Nat Rev Gen*)
- microarray scan via 1 QTL interval mapping
 - Brem et al. (2002 *Science*); Schadt et al. (2003 *Nature*); Yvert et al. (2003 *Nat Gen*)
 - found putative *cis*- and *trans*- acting genes
- multivariate and multiple QTL approach
 - Lan et al. (2003 *Genetics*)

central dogma via microarrays (Bochner 2003)



Nature Reviews | Genetics

idea of mapping microarrays (Jansen Nap 2001)



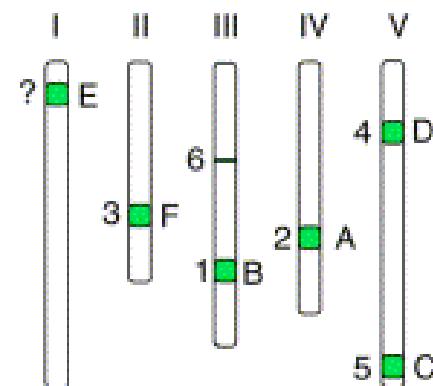
goal: unravel biochemical pathways (Jansen Nap 2001)

(a) Marker

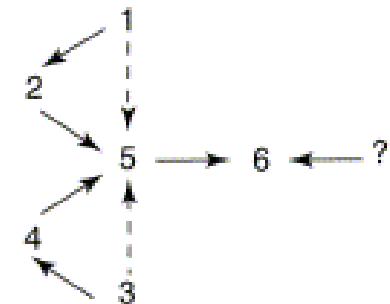
		A	B	C	D	E	F	...	all
cDNA	1	*							
	2	*	*						
	3								
	4			*		*			
	5	*	*	*	*	*			
	6	*	*	*	*	*	*		
	...								
	all								

+

(b) Map positions



(c) One putative pathway



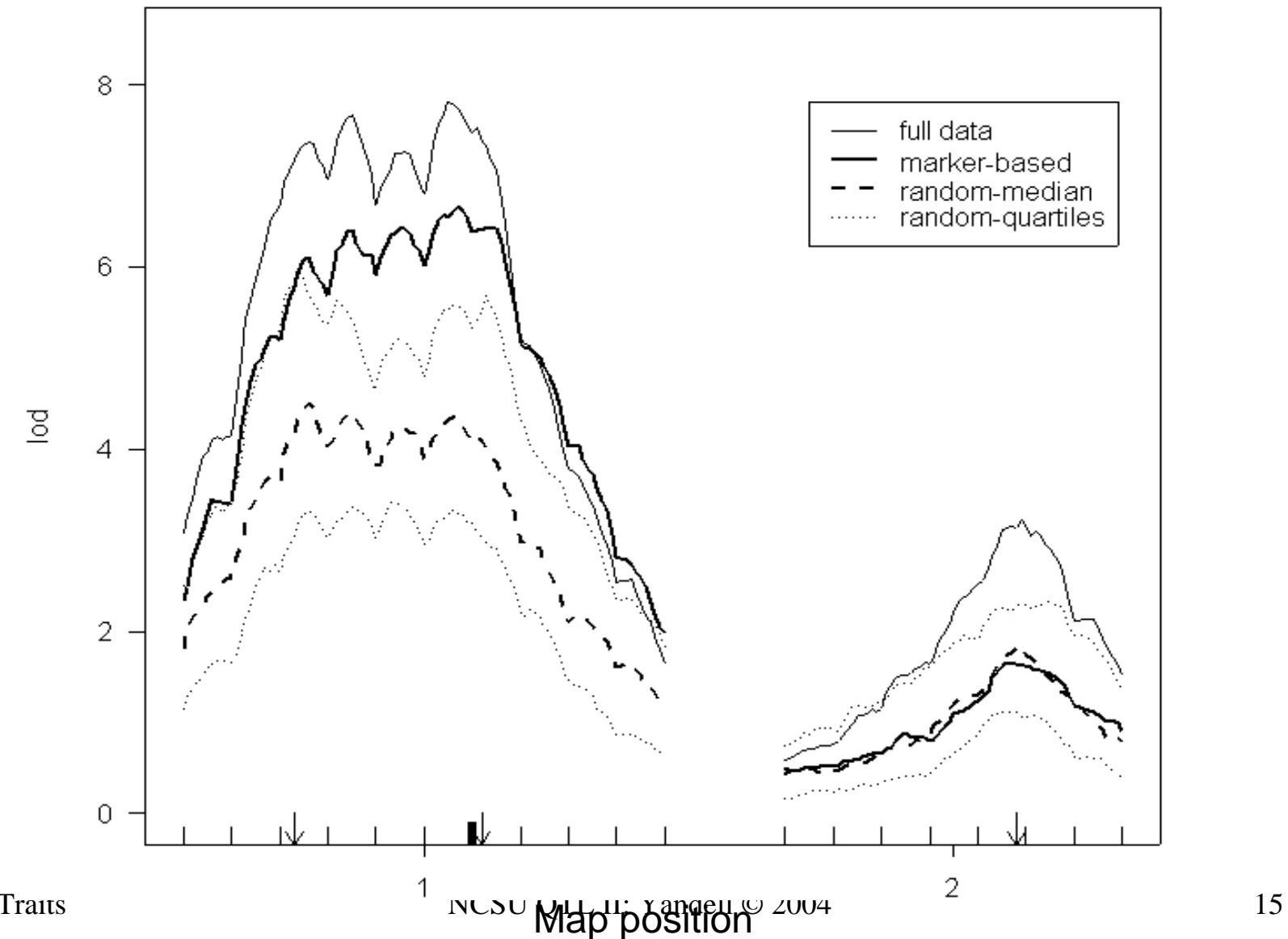
TRENDS in Genetics



2. design issues for expensive phenotypes (thanks to CF “Amy” Jin)

- microarray analysis ~ \$1000 per mouse
 - can only afford to assay 60 of 108 in panel
 - wish to not lose much power to detect QTL
- selective phenotyping
 - genotype all individuals in panel
 - select subset for phenotyping
 - previous studies can provide guide

simulated LOD profiles with 3 QTL

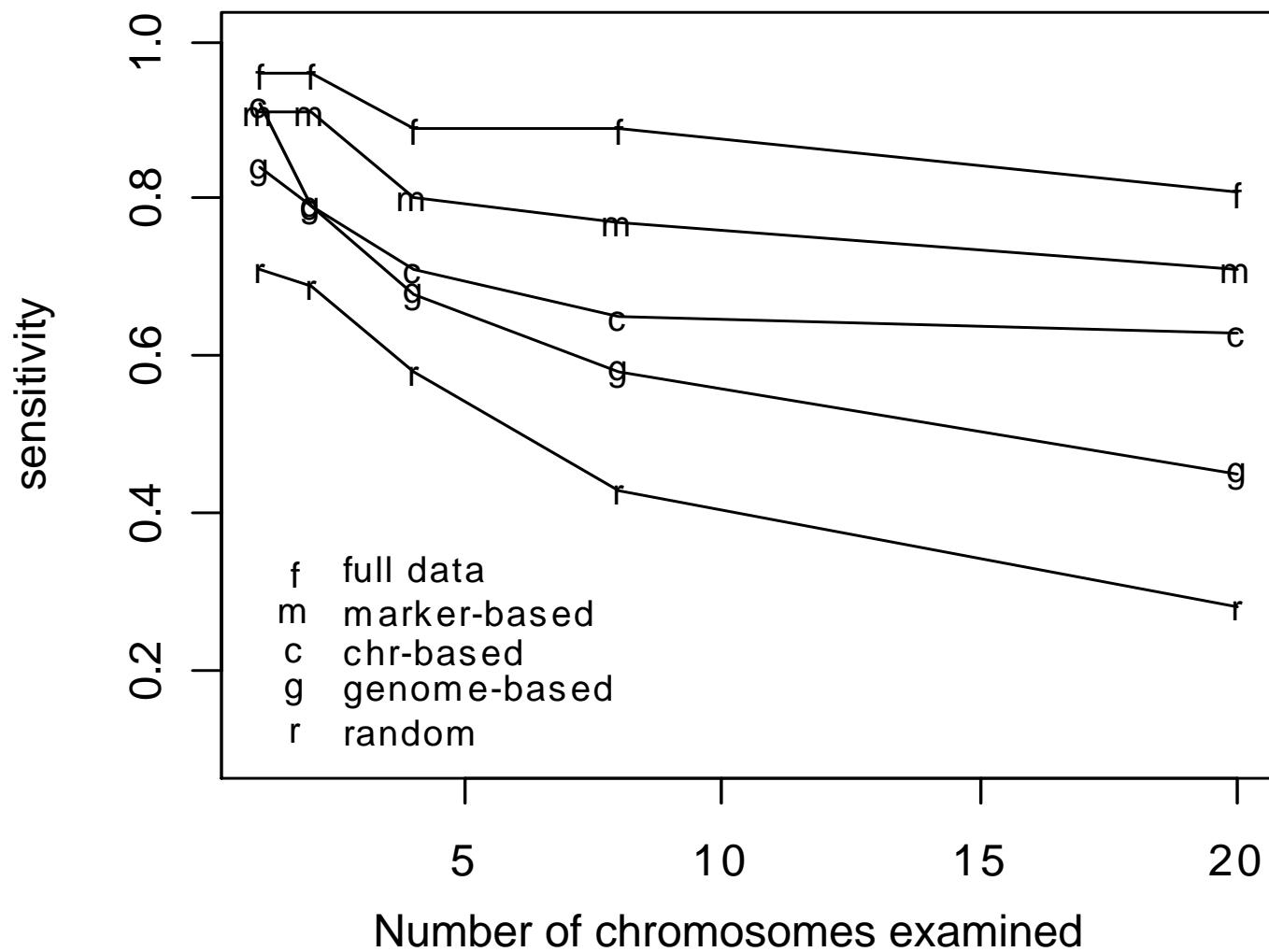


selective phenotyping

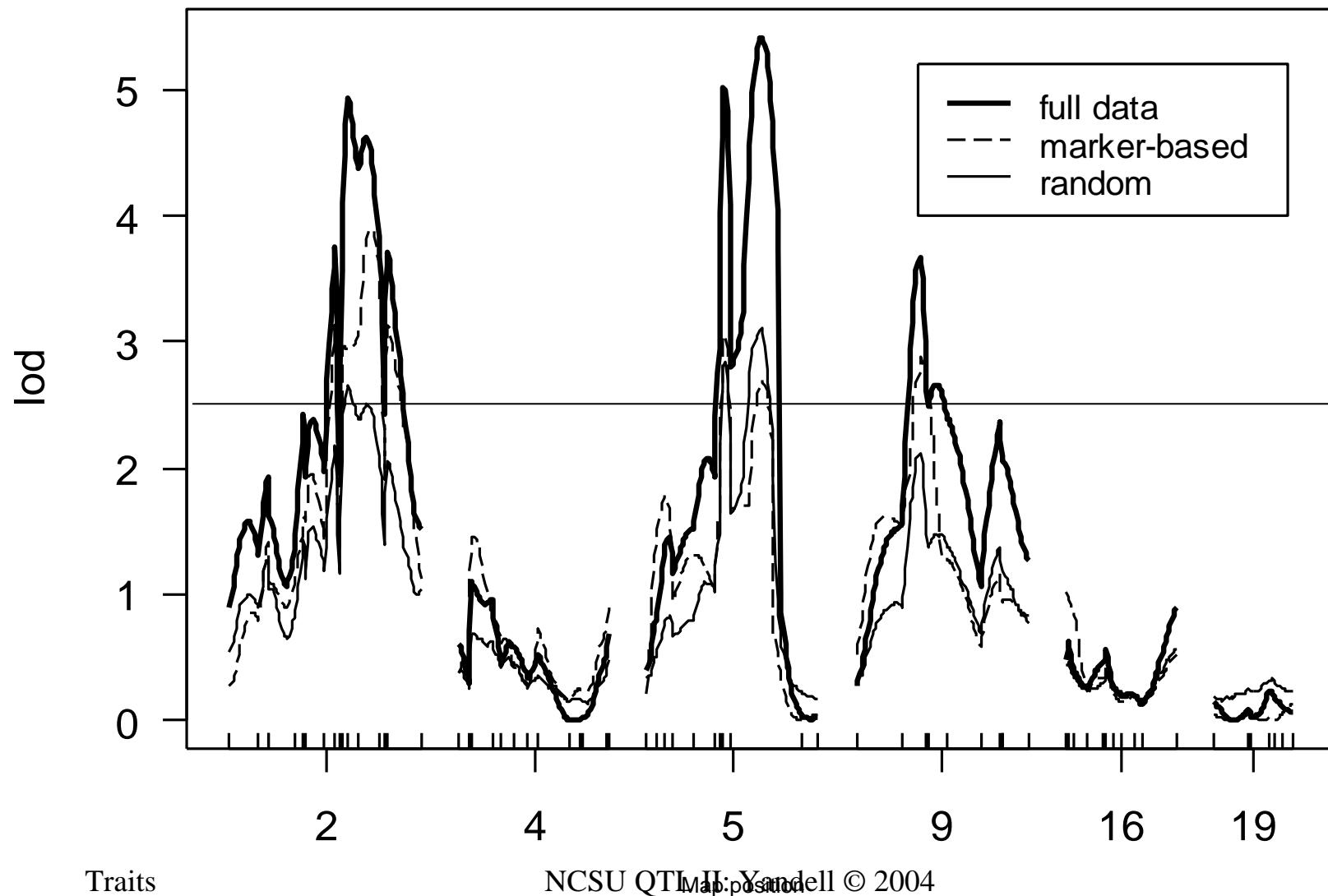
- genotype all individuals in panel
 - whole genome or selected genomic regions?
 - maintain high power in selected regions
 - sensitivity similar to random sample in other regions
- select subset for phenotyping
 - select individuals with large genetic distance
 - use experimental design concepts (Jin et al. 2004)
- previous studies: key regions of chr 2,4,5,9,16,19
 - QTL for important physiological traits

comparison of different selection methods

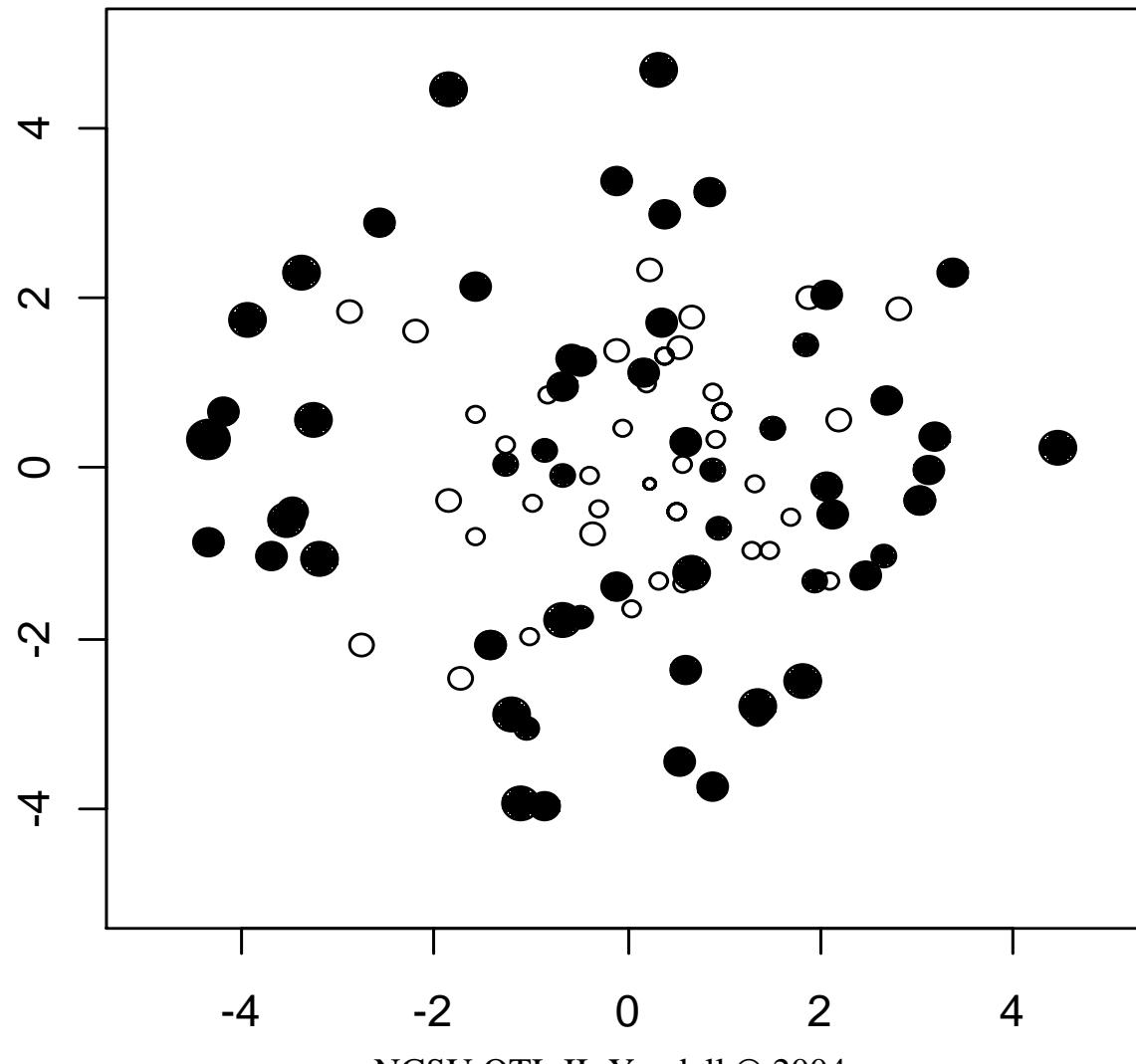
sensitivity = $\text{pr}(\text{ detect QTL} \mid \text{QTL is real})$



LOD profile of SCD trait



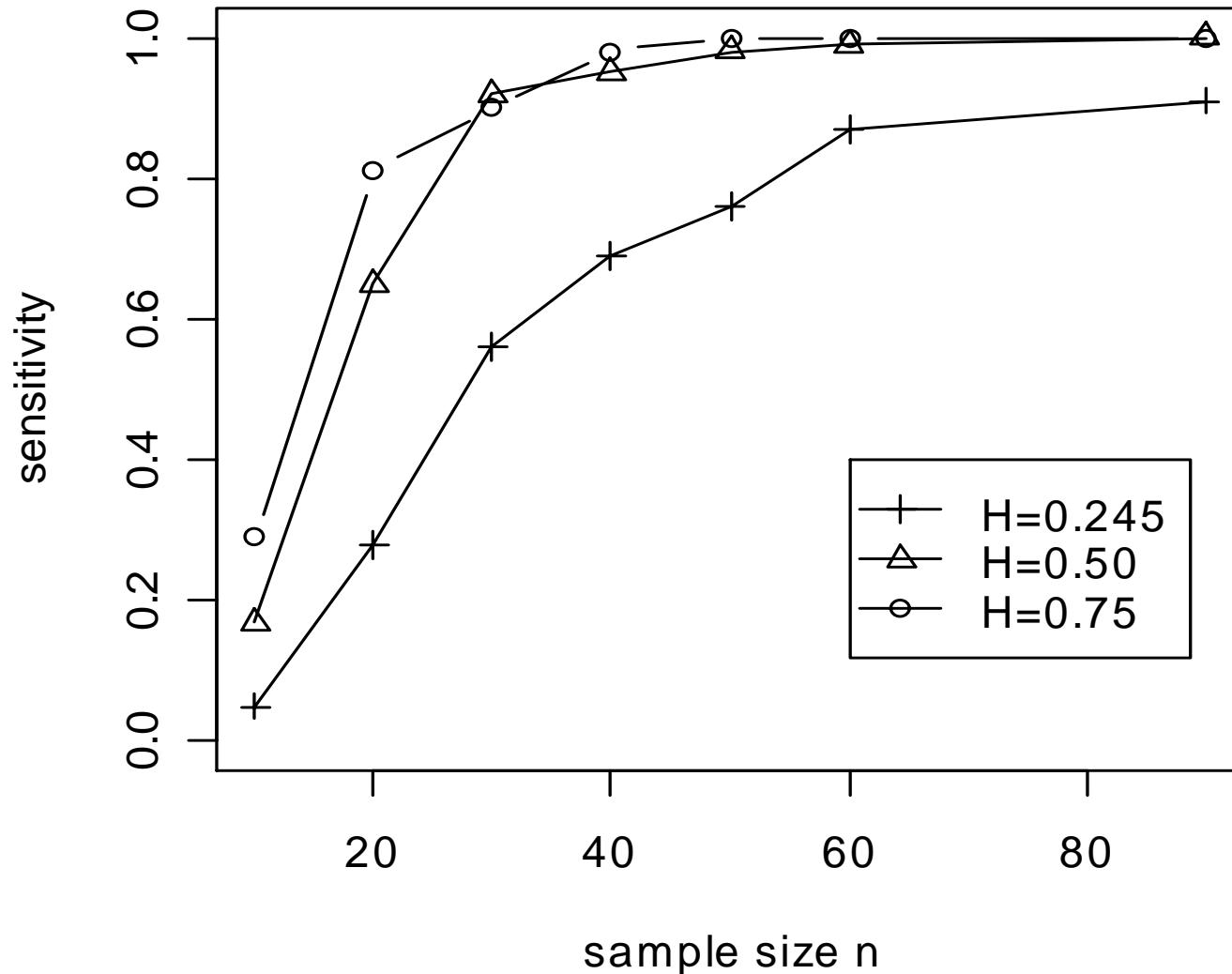
multidimensional scaling of mice selection (close points have similar genotypes)



is this relevant to large QTL studies?

- why not phenotype entire mapping panel?
 - selectively phenotype subset of 50-67%
 - may capture most effects
 - with little loss of power
- two-stage selective phenotyping?
 - genotype & phenotype subset of 100-300
 - could selectively phenotype using whole genome
 - QTL map to identify key genomic regions
 - selectively phenotype subset using key regions

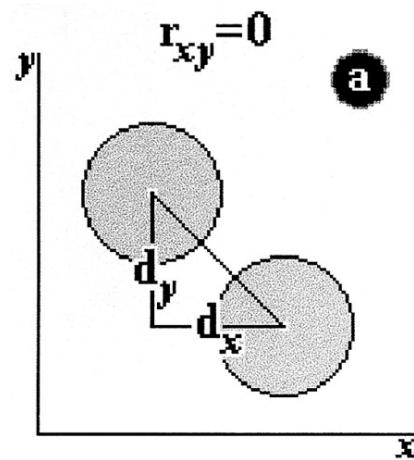
$\text{sensitivity} = \text{pr}(\text{ detect QTL} \mid \text{QTL is real})$
depends on heritability and proportion sampled (of $N=100$)



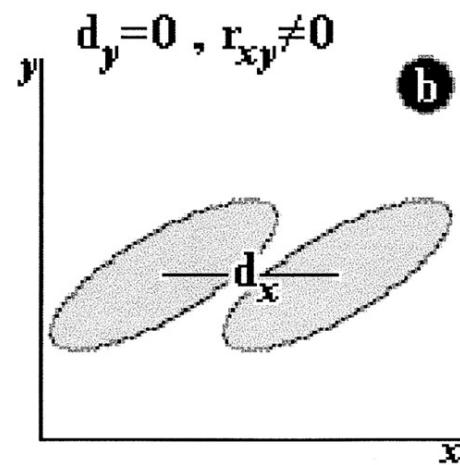
3. why are traits correlated?

- environmental correlation
 - non-genetic, controllable by design
 - historical correlation (learned behavior)
 - physiological correlation (same body)
- genetic correlation
 - pleiotropy
 - one gene, many functions
 - common biochemical pathway, splicing variants
 - close linkage
 - two tightly linked genes
 - genotypes Q are collinear

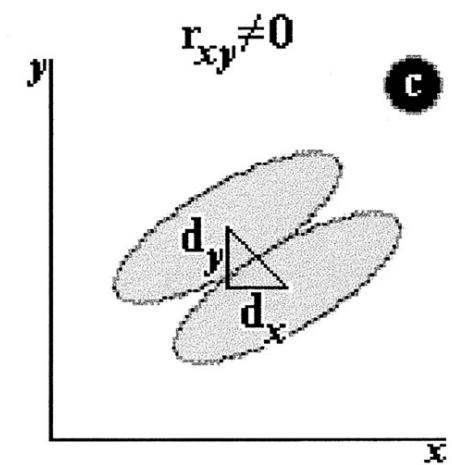
interplay of pleiotropy & correlation



pleiotropy only



correlation only
Korol et al. (2001)



both

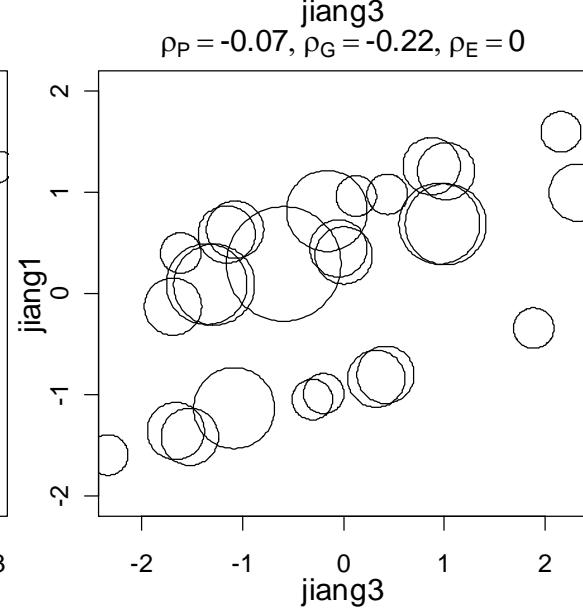
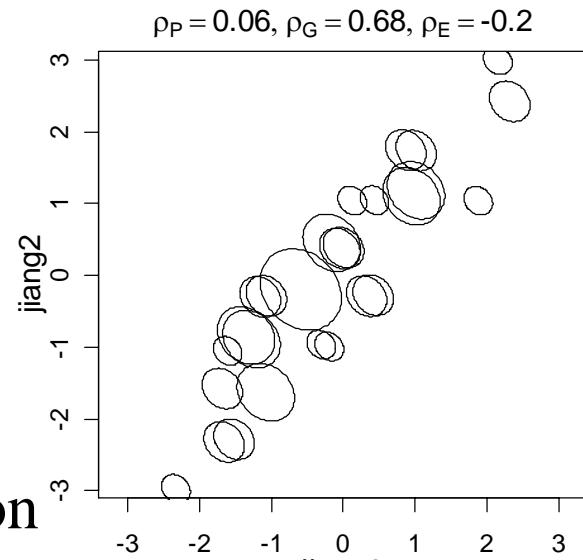
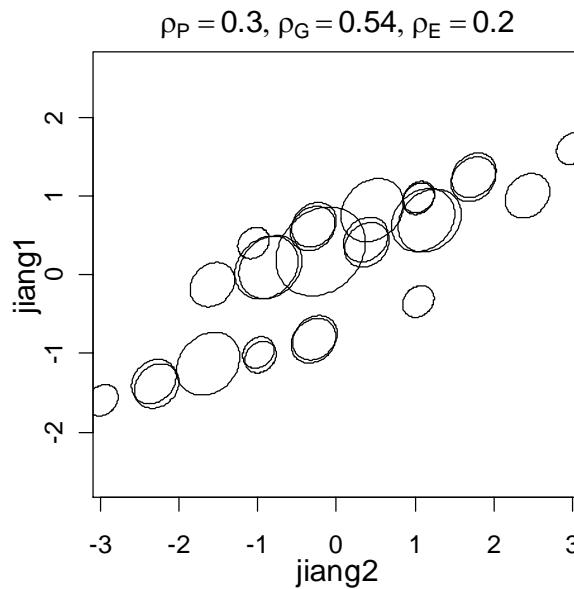
3 correlated traits (Jiang Zeng 1995)

ellipses centered on genotypic value
width for nominal frequency
main axis angle environmental correlation

3 QTL, F2

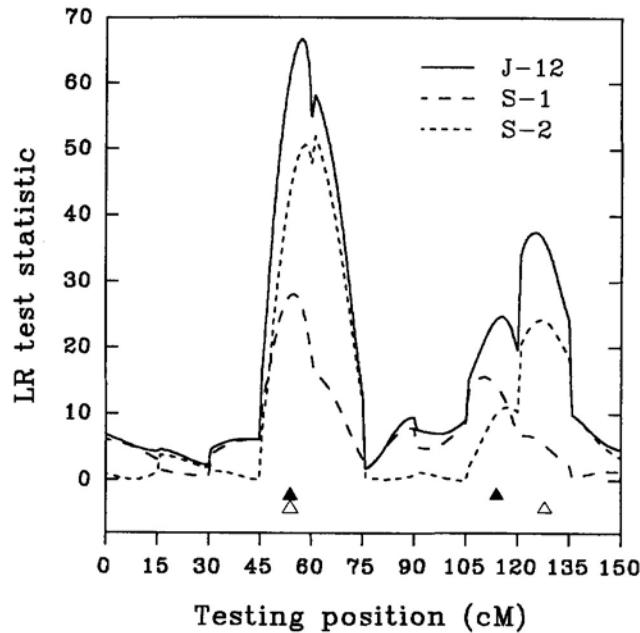
27 genotypes

note signs of
genetic and
environmental
correlation



pleiotropy or close linkage?

2 traits, 2 qtl/trait
pleiotropy @ 54cM
linkage @ 114,128cM
Jiang Zeng (1995)



Traits

NCSU QTL II: Yandell © 2004

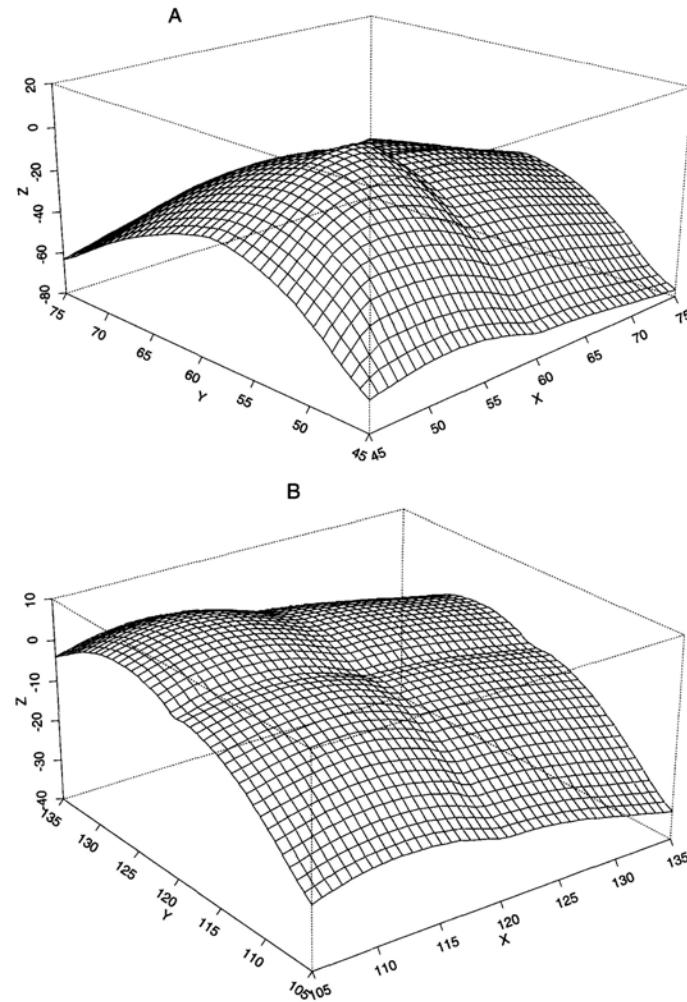
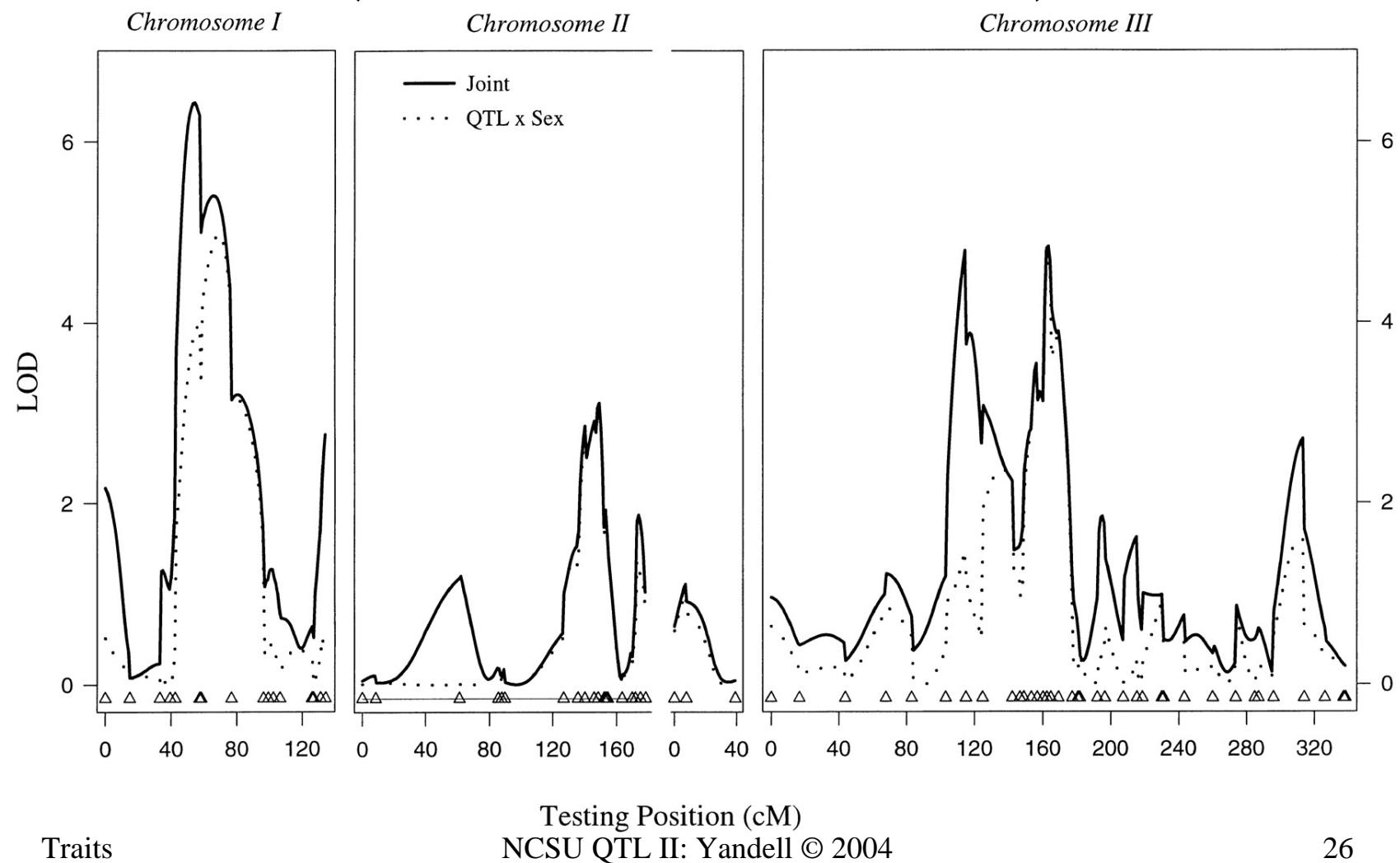


FIGURE 2.—Two-dimensional log-likelihood surfaces (expressed as deviations from the maximum of the log-likelihoods on the diagonal) for the test of pleiotropy vs. close linkage are presented for two regions: the region between 45 and 75 cM of Figure 1(A) and the region between 105 and 135 cM (B). X is the testing position for a QTL affecting trait 1 and Y is the testing position for a QTL affecting trait 2. On the diagonal of $X-Y$ plane, two QTL are located in the same position and statistically are treated as one pleiotropic QTL. Z is the likelihood ratio test statistic scaled to zero at the maximum point of the diagonal.

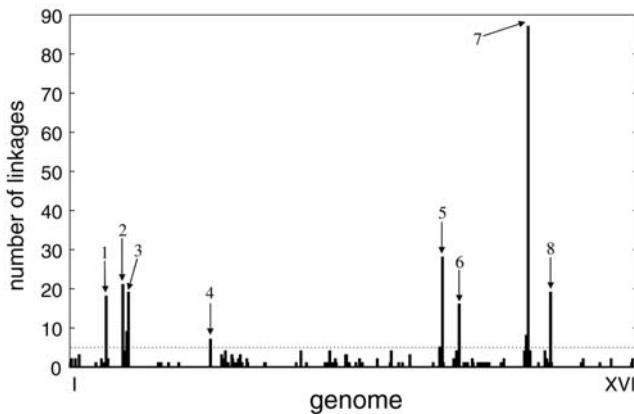
QTL x sex interaction (Vieira et al. 2000)



4. high throughput dilemma

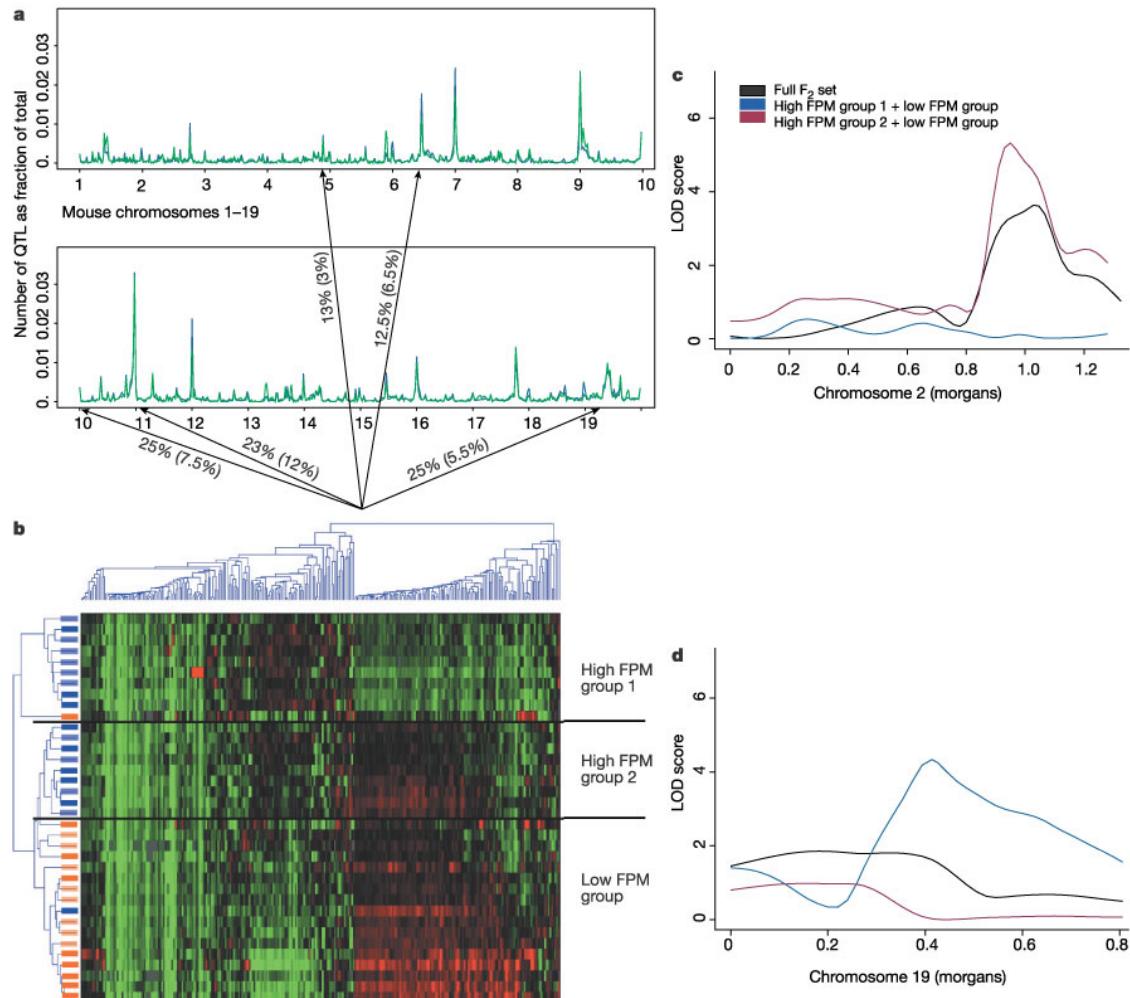
- want to focus on gene expression network
 - ideally capture pathway in a few dimensions
 - allow for complicated genetic architecture
- may have multiple controlling loci
 - could affect many genes in coordinated fashion
 - could show evidence of epistasis
 - quick assessment via interval mapping may be misleading
- try mapping principle components as super-trait
 - capture key multivariate features of multiple traits
 - elicit biochemical pathways (Henderson et al. Hoeschele 2001; Ong Page 2002)

expression
pleiotropy
in yeast genome
(Brem et al. 2002)



Traits

coordinated expression in mouse genome (Schadt et al. 2003)

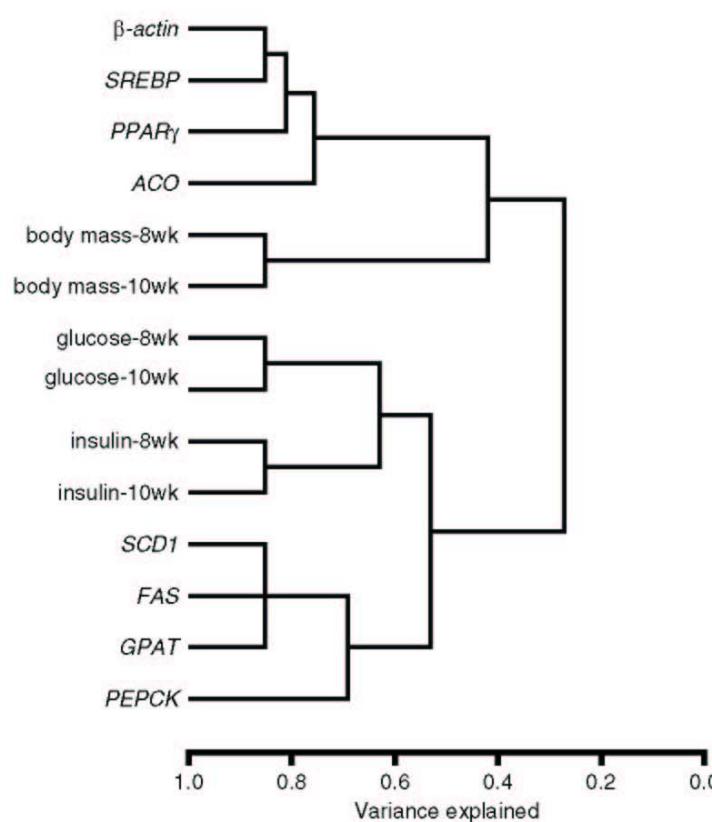


NCSU QTL II: Yandell © 2004

28

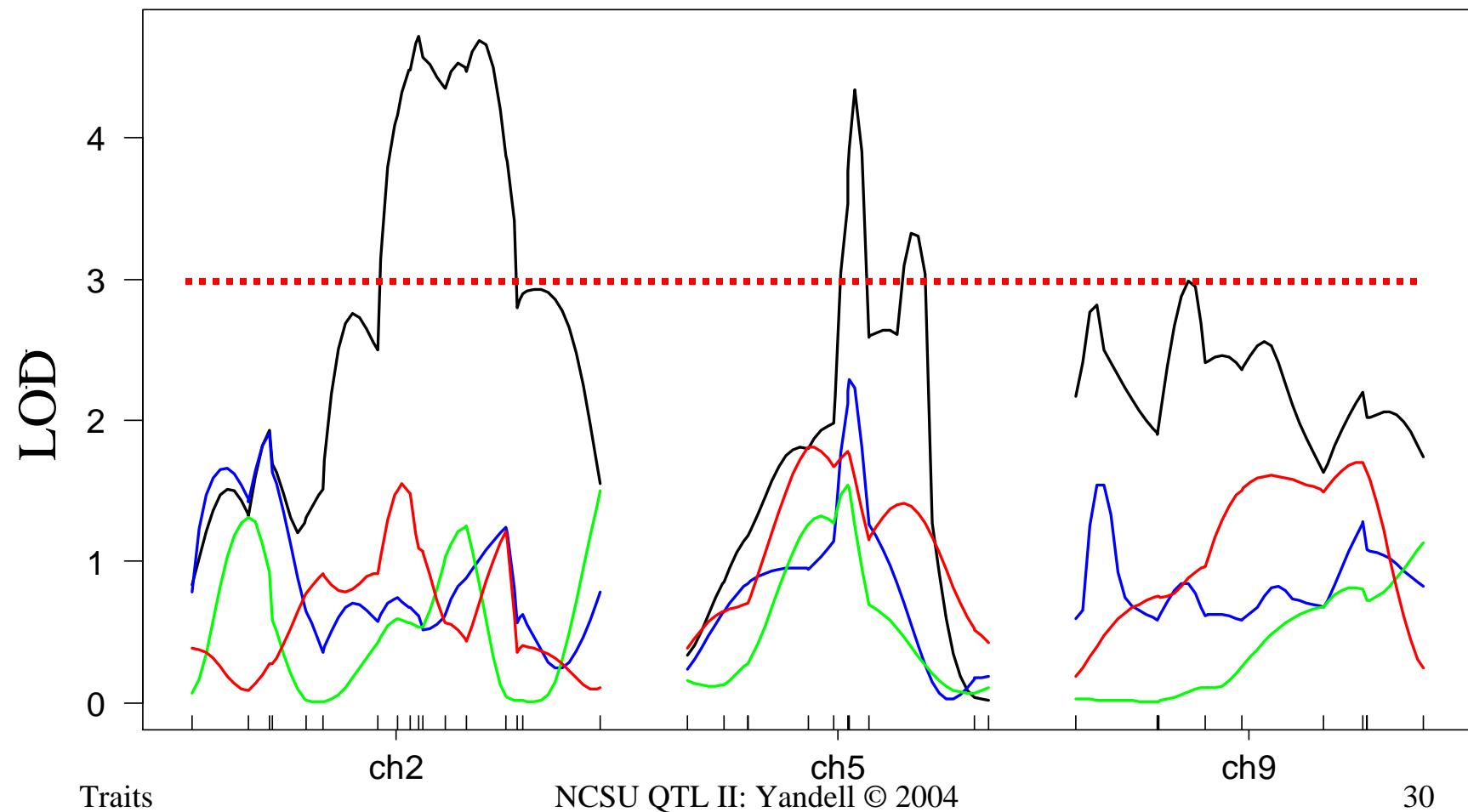
high throughput: which genes are the key players?

Lan et al., mapping mRNA, Figure 2



- clustering of expression seed by insulin, glucose
- advantage: subset relevant to trait
- disadvantage: still many genes to study

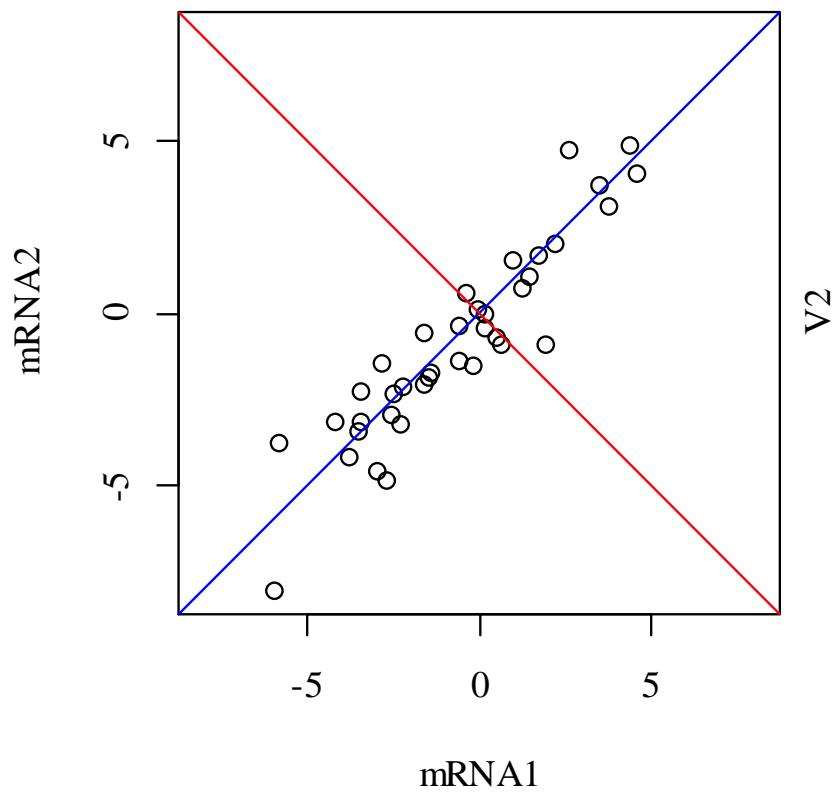
SCD1, FAS,GPAT, PEPCK: *trans*-regulation by multiple QTL?



from gene expression to super-genes

- PC or SVD decomposition of multiple traits
 - $Y = t \text{ traits} \times n \text{ individuals}$
 - decompose as $Y = U D W^T$
 - U, W = ortho-normal transforms (eigen-vectors)
 - D = diagonal matrix with singular values
- transform problem to principal components
 - W_1 and W_2 uncorrelated "super-trait"
- interval map each PC separately
 - $W_1 = \mu^*_1 + G^*_{1Q} + e^*_1$
- may only need to map a few PCs

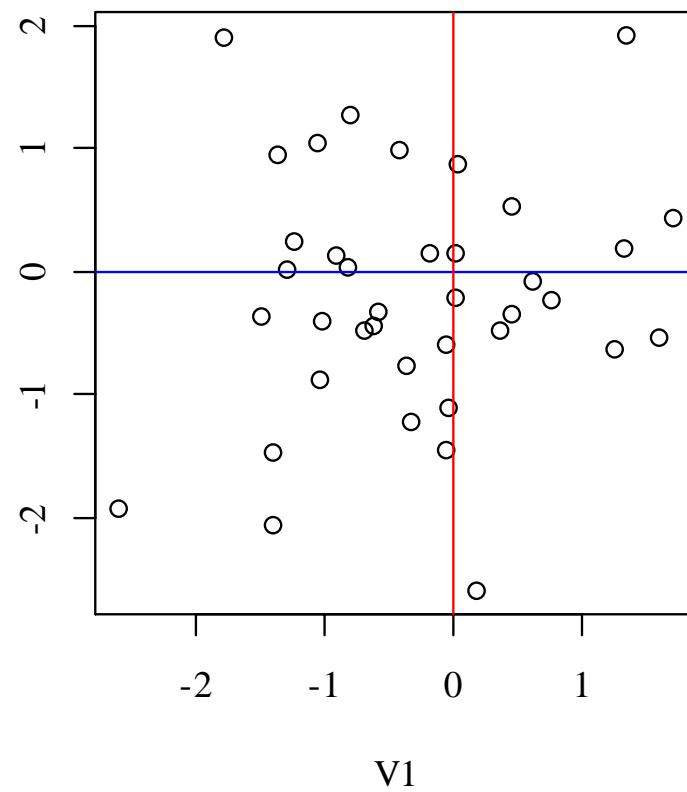
PC simply rotates & rescales
to find major axes of variation



Traits

NCSU QTL II: Yandell © 2004

V2



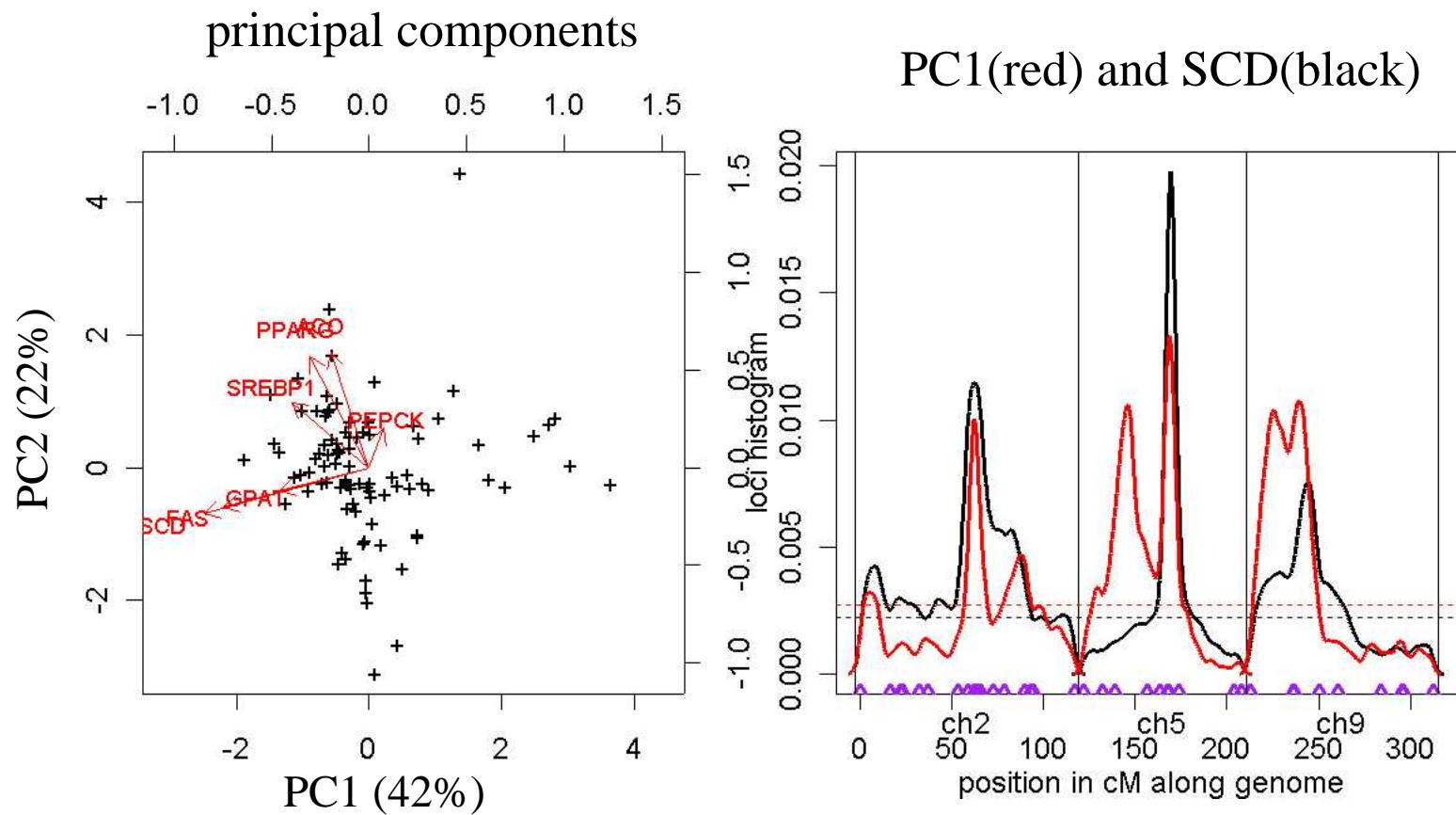
V1

32

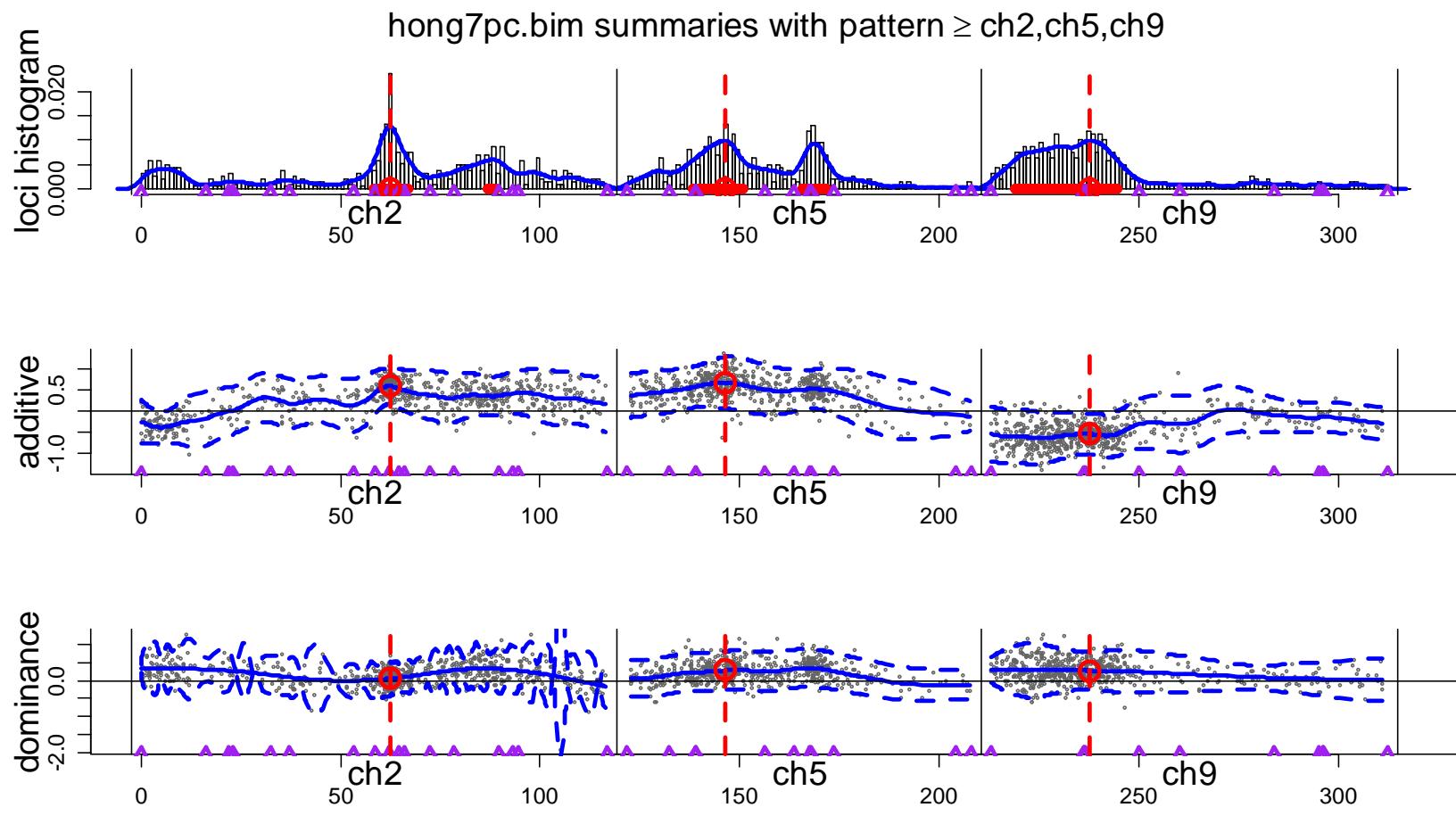
QTL via Principal Components

- *Drosophila* gonad shape
 - Liu et al. (1996); Zeng et al. (2000)
- other refs of interest
 - Weller et al. (1996); Mangin et al. (1998); Olson et al. (1999); Mahler et al. (2002)
- problems
 - PC may have no relation to genetics!
 - residuals from QTL correlated across PCs
 - PC is descriptive summary, not interpretive

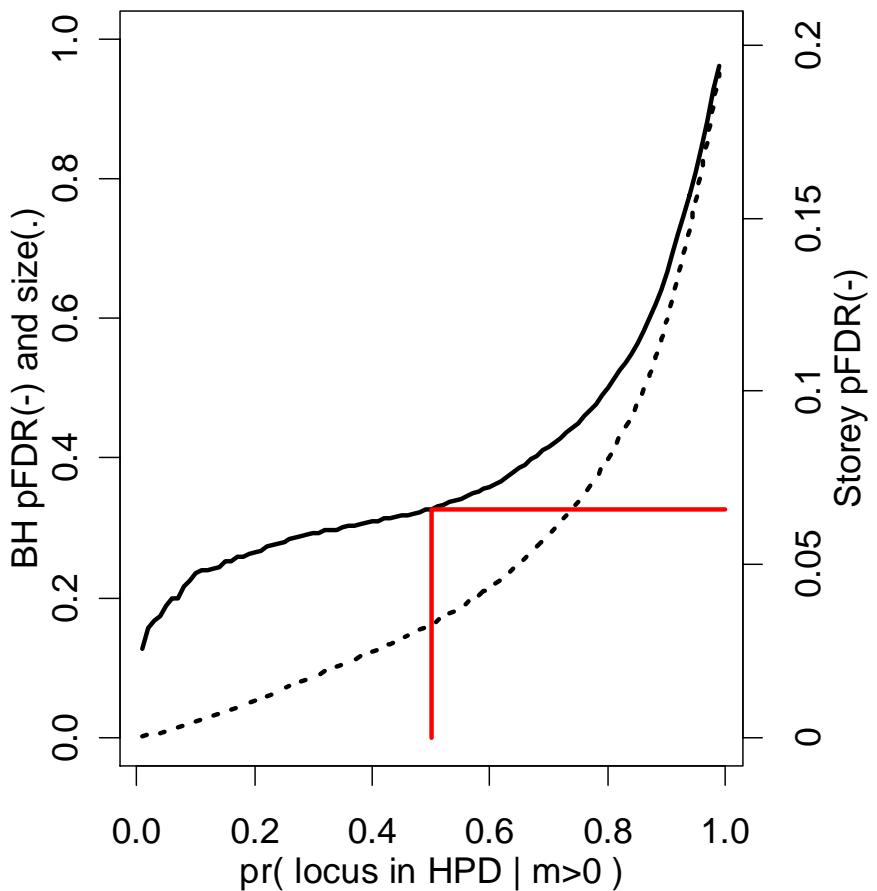
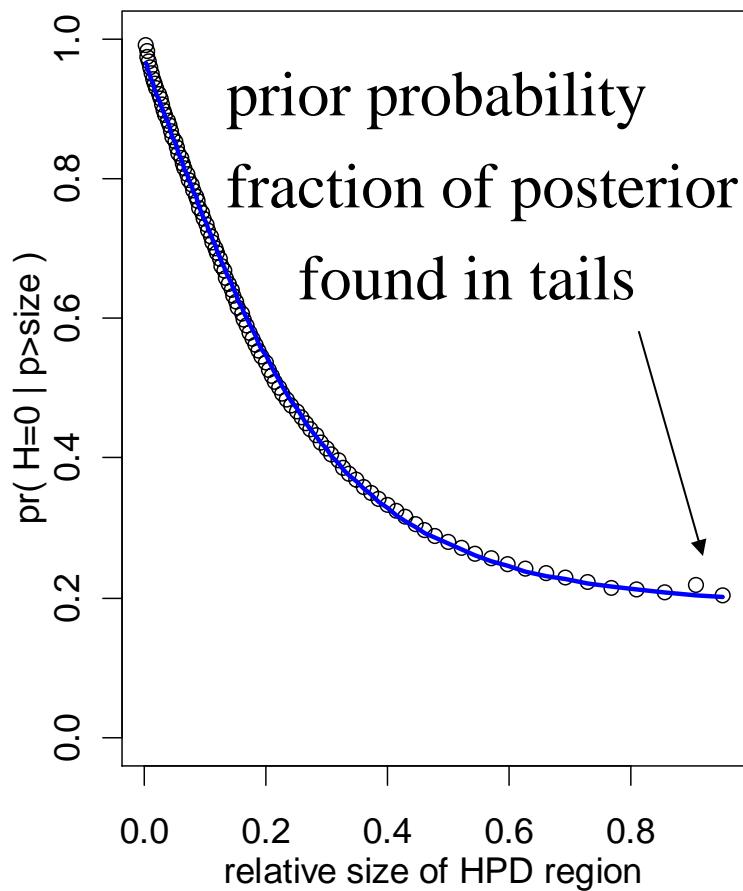
multivariate screen for gene expressing mapping



mapping first diabetes PC as a trait



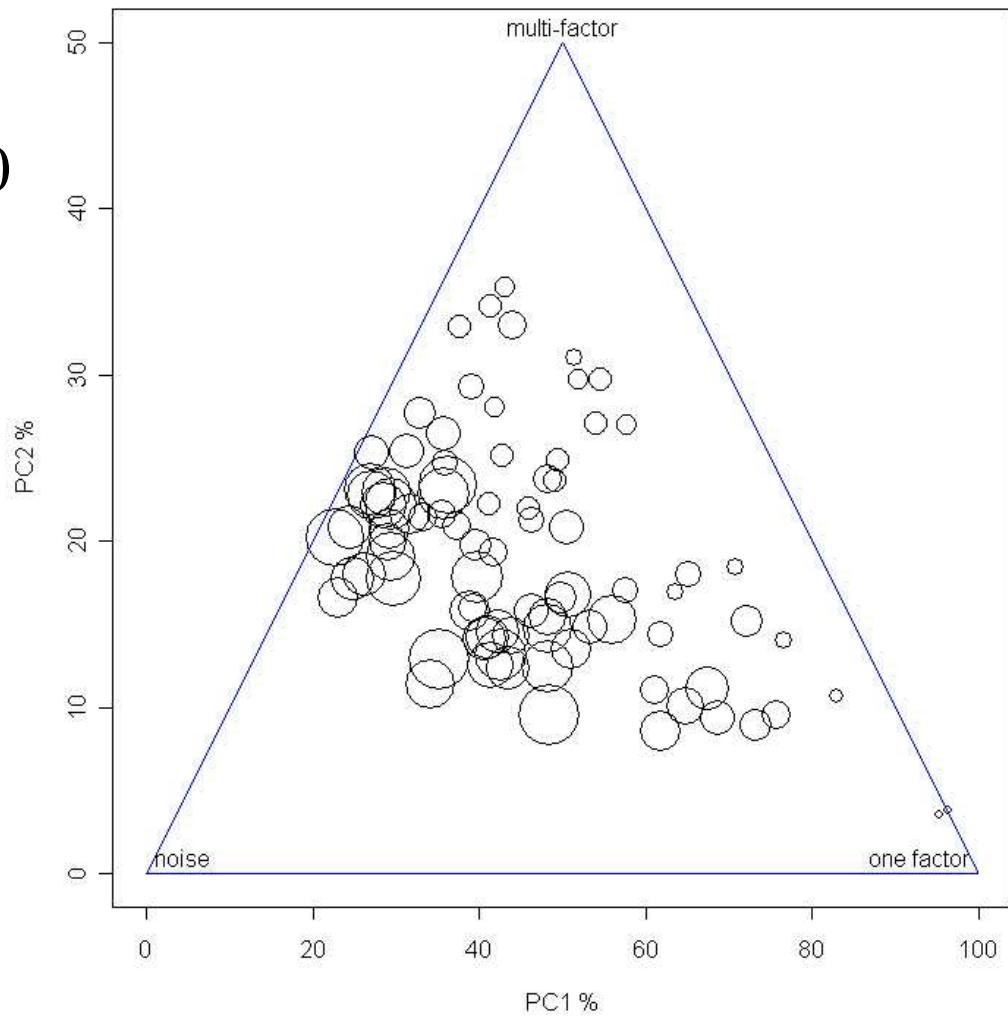
pFDR for PC1 analysis



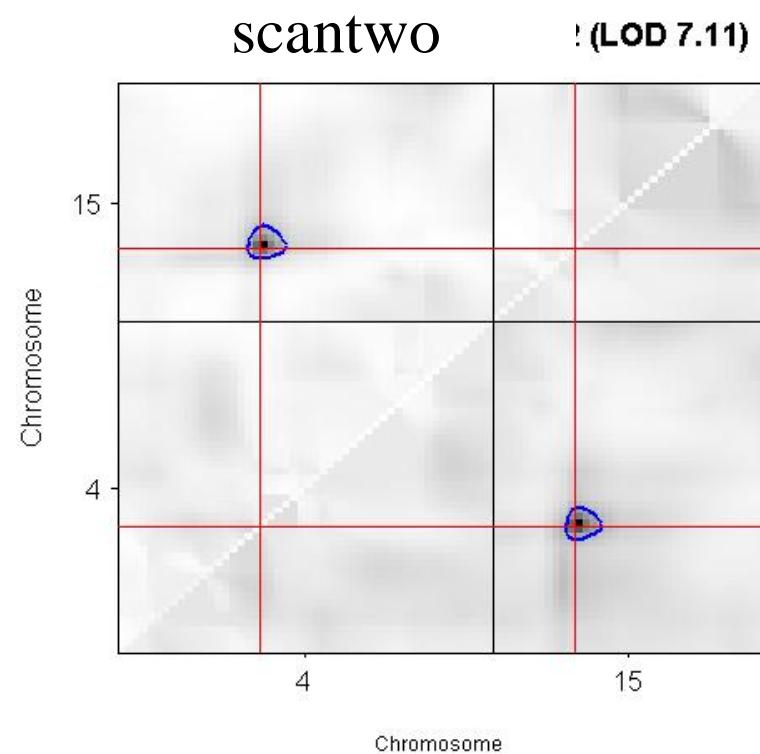
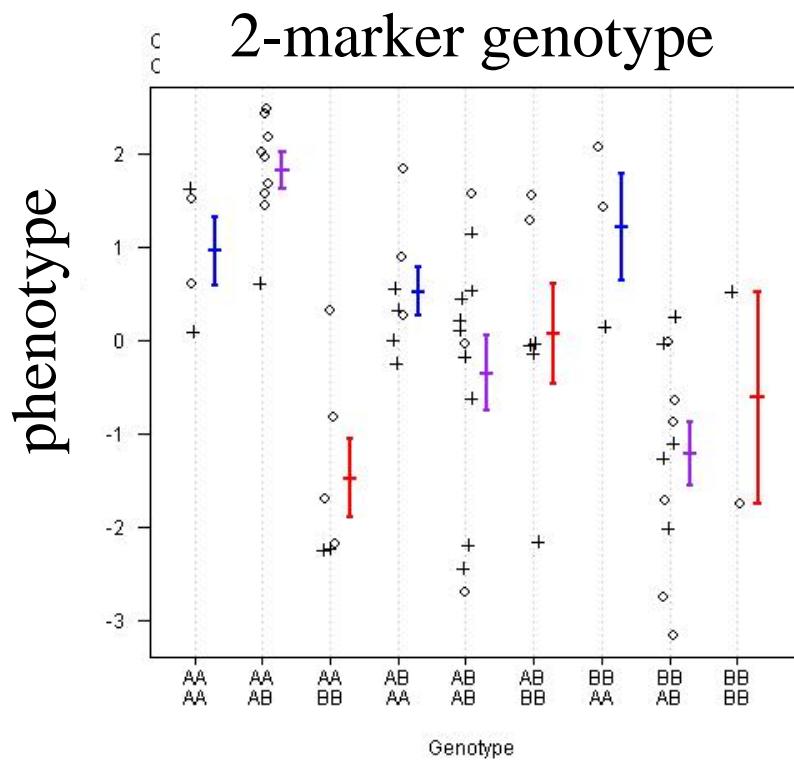
PC across microarray functional groups

1500+ mRNA of 30,000
85 functional groups
60 mice
2-35 mRNA / group
which are interesting?

examine PC1, PC2
size = # unique mRNA

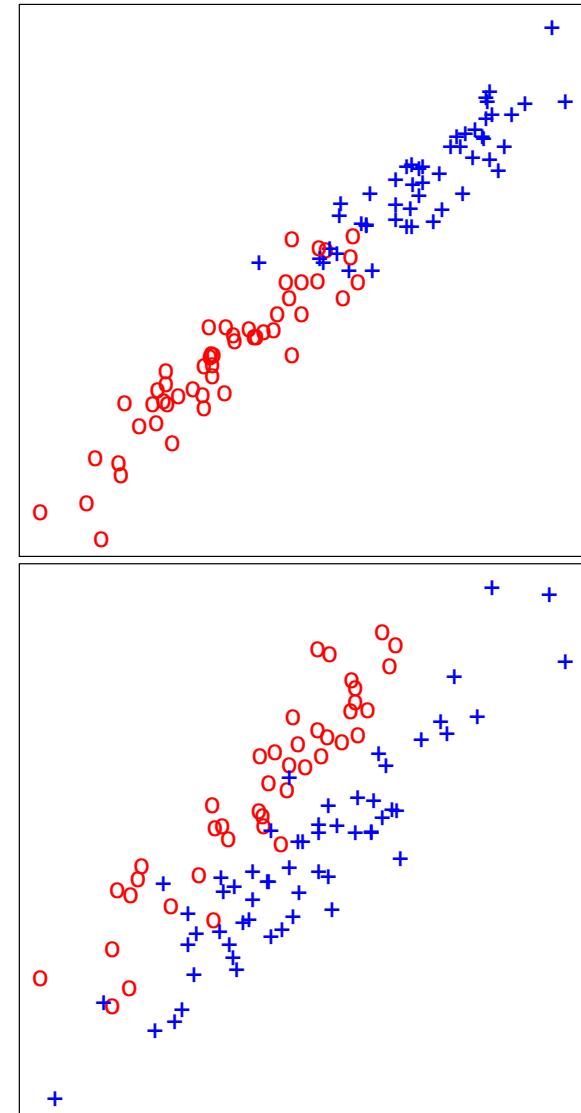


PC-guided search of mRNA (red lines at main QTL for PC1)



improvements on PC?

- what is our goal?
 - reduce dimensionality
 - focus on QTL
- PC reduces dimensionality
 - but may not relate to genetics
- canonical discriminant analysis
 - rotate to improve discrimination
 - redo at each putative QTL
 - Gilbert and le Roy (2003,2004)



how to map multiple traits?

- WinQTL/QTL Cartographer: IM & CIM
 - Jiang Zeng (1995); statgen.ncsu.edu/qtlcart
- MultiQTL: 1-2 QTL with PC on residuals
 - Korol et al. (2001); www.multiqtl.com
- 1-2 QTL with DA across traits
 - Gilbert and le Roy (2003, 2004)
- QTL Express: Haley-Knott regression
 - Knott Haley (2000); qtl.cap.ed.ac.uk
- SOLAR: outbred pedigrees
 - Almasy Blangero (1997); Williams et al. (1999)