Sample mix-ups in eQTL data

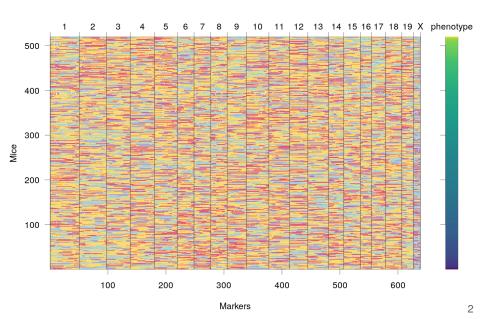
Karl Broman

Biostatistics & Medical Informatics, UW-Madison

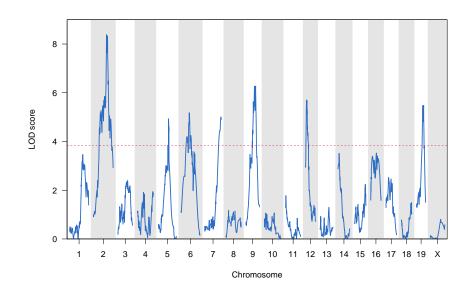
kbroman.org github.com/kbroman @kwbroman

Course web: kbroman.org/AdvData

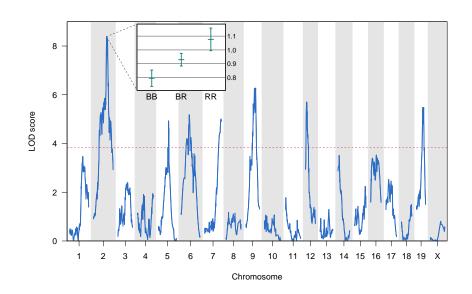
Data



QTL mapping



QTL mapping



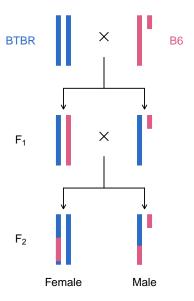
Attie project

 \sim 500 B6 \times BTBR intercross mice, all ob/ob

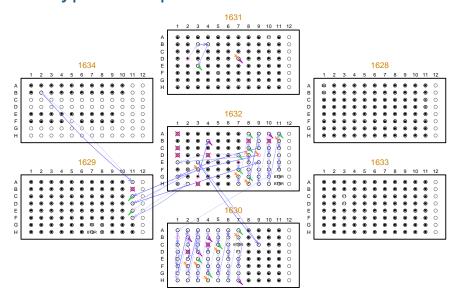
- Genotypes at 2057 SNPs (Affymetrix arrays)
- ► Gene expression in six tissues (Agilent arrays)
 - adipose
 - gastrocnemius muscle
 - hypothalamus
 - pancreatic islets
 - kidney
 - liver
- Numerous clinical phenotypes

(e.g., body weight, insulin and glucose levels)

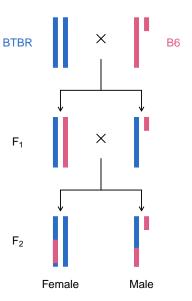
Sex and the X chr



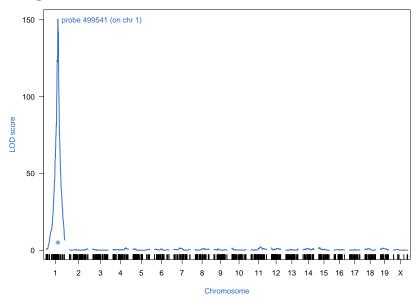
Genotype mix-ups



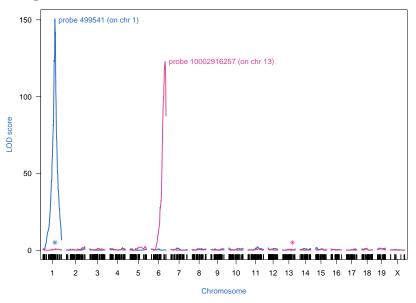
Sex and the X chr

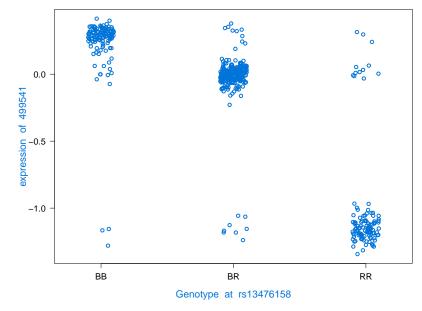


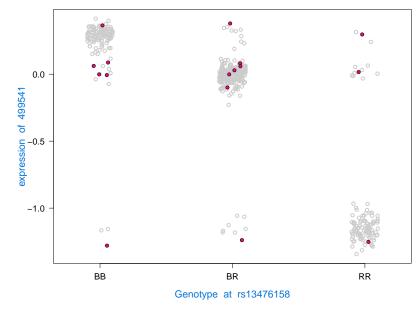
Strong eQTL



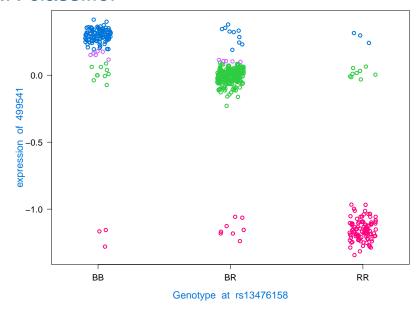
Strong eQTL

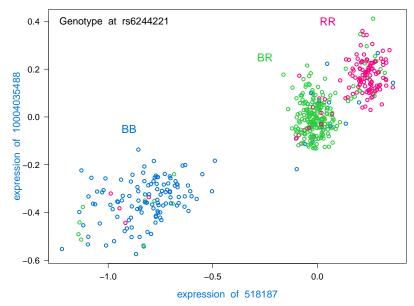


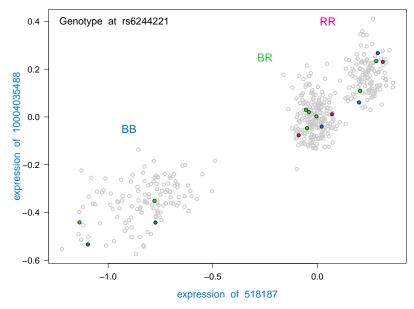


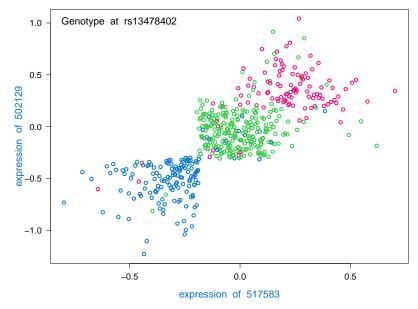


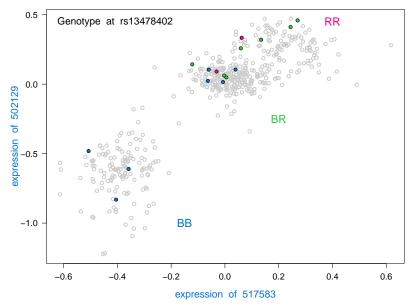
kNN classifier

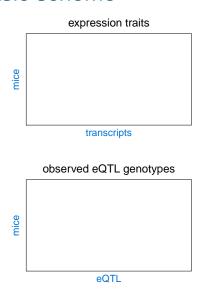


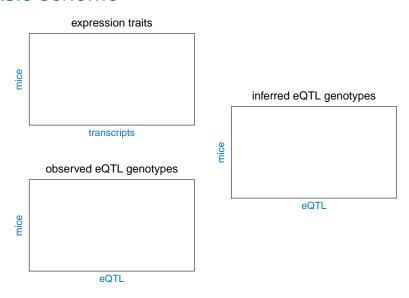


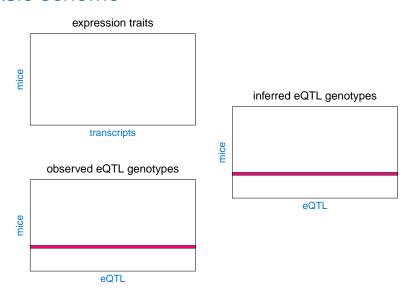


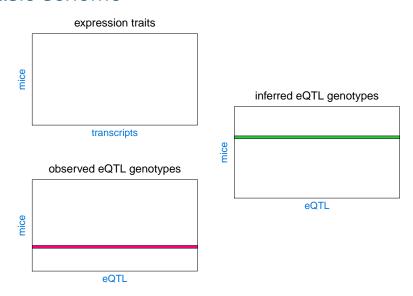


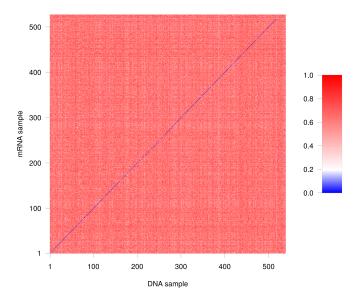


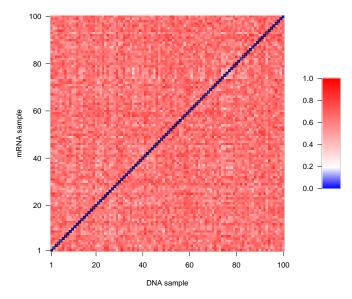


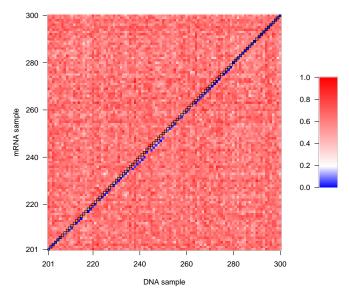


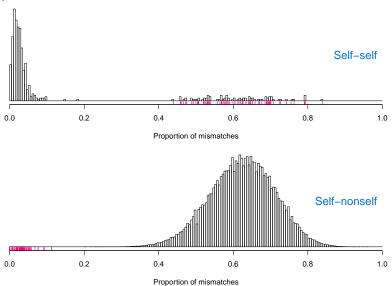




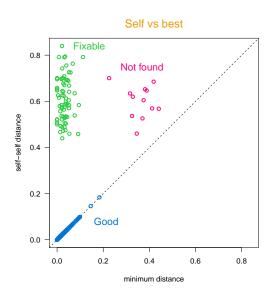








Decisions



Genotype mix-ups

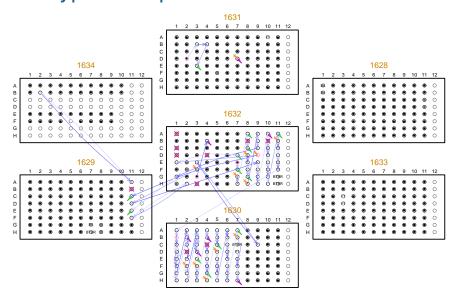
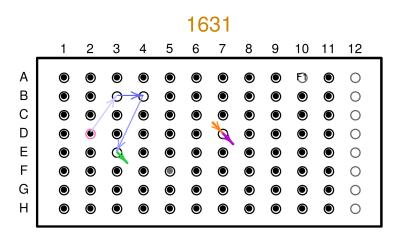


Plate 1631



Plates 1632 and 1630

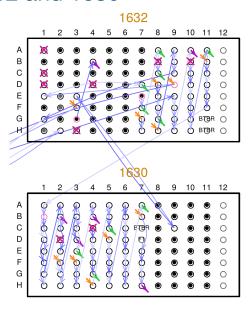
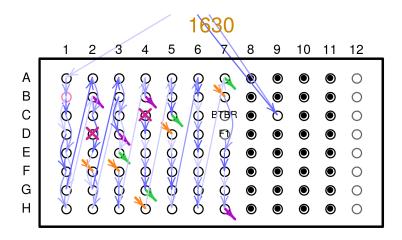
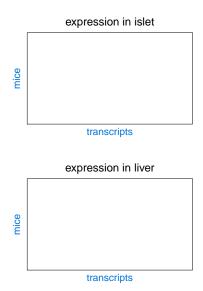
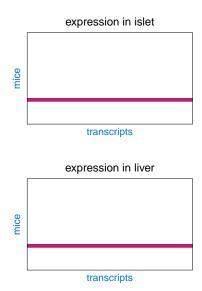
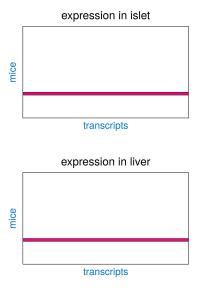


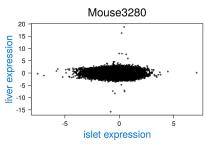
Plate 1630

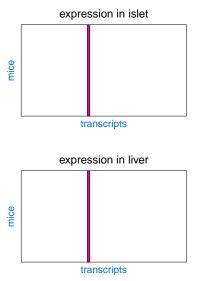


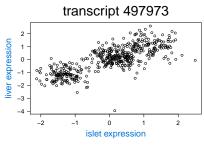


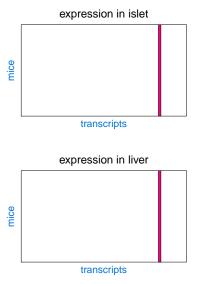


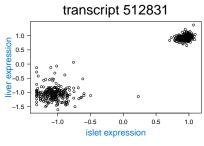


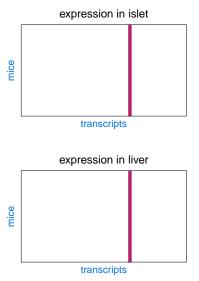


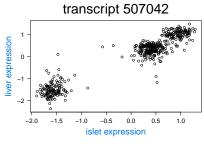


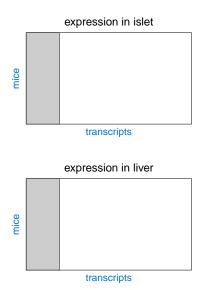


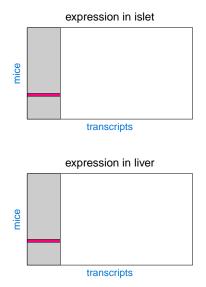


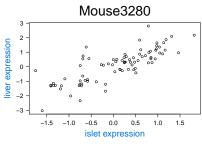


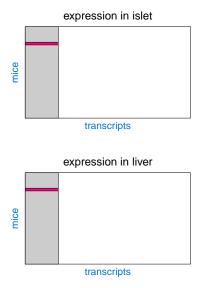


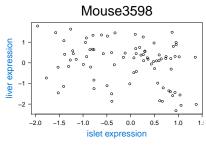


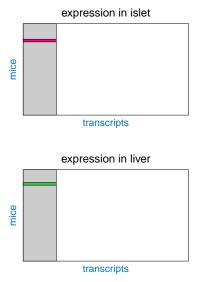


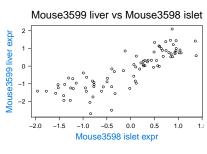


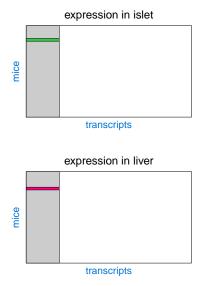


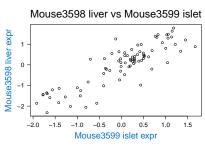


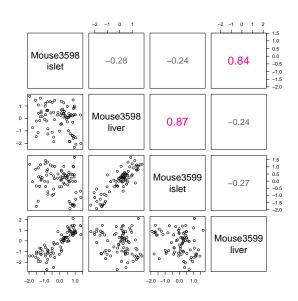


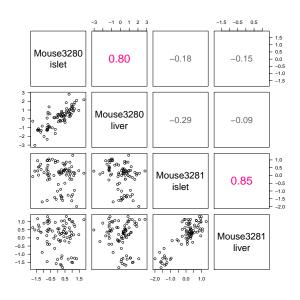


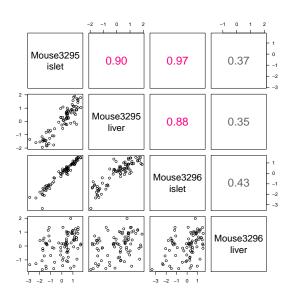






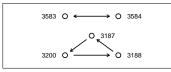




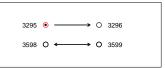


Expression mix-ups

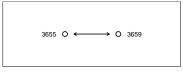
adipose



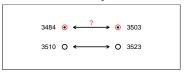
islet



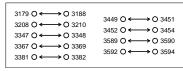
gastroc



kidney



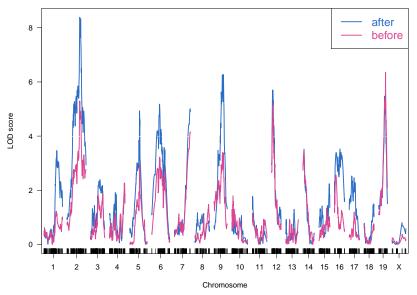
hypo



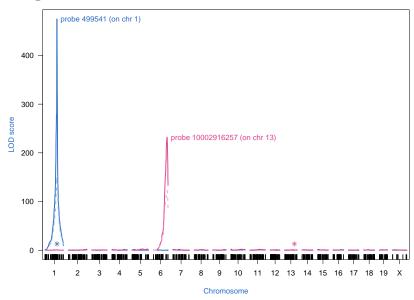
liver



Insulin QTL



Strong eQTL



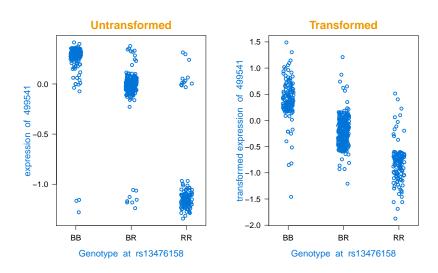
Summary

- ► Sample mix-ups happen
- With eQTL data, we can both identify and correct mix-ups
- There is great value in having expression on multiple tissues
- The general idea here has wide application for high-throughput data
- ► Broman et al. (2015) G3 5:2177-2186 doi: 10.1534/g3.115.019778
- Related work:
 - Westra et al. (2011) Bioinformatics 27:2104–2111
 - Schadt et al. (2012) Nat Genet 44:603–608
 - Ekstrøm and Feenstra (2012) Stat Appl Genet Mol Biol 3:Article 13
 - Lynch et al. (2012) PLoS ONE 7:e41815

Lessons

- Don't fully trust anyone
 - Including yourself
- Make lots of plots
 - Don't rely on summary statistics, like LOD scores
 - Look at responses on the original scale
- Follow up all aberrations
- Take your time with data cleaning
 - A month, two months, a year?
- If you have big rectangles whose rows correspond, check that they actually correspond

E vs G



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Decisions

