



Data Quality Control (QC) in Association Studies

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- Assess data quality to remove sub-standard genotypes, samples and SNPs from subsequent association analysis





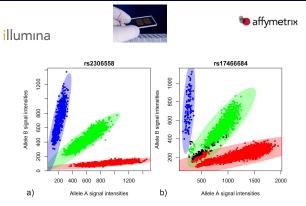
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- Tutorials
 - ► Anderson et al. Nature Protocols 2010, doi:10.1038/nprot.2010.116
 - ► Turner et al. Curr Protoc Hum Genet. 2011. doi:10.1002/0471142905.hg0119s68
 - ▶ Marees et al. Int J Methods Psychiatr Res. 2018. doi: 10.1002/mpr.1608











- Examples of cluster plots for two SNPs. One spot corresponds to one sample.
- Samples with genotypes AA and BB are red and blue, respectively. Heterozygous samples
 are shown in green; samples with missing genotypes are black. The ellipses represent the
 cluster boundaries as computed by ACPA.
- a) No samples in overlapping ellipses;
 b) Red samples lie in the green ellipse. At the bottom of the green ellipse, samples have been erroneously classified as red samples.

Schillert et al. BMC Proceedings 2009, 3(Suppl 7):S58 doi: 10.1186/1753-6561-3-S7-S58

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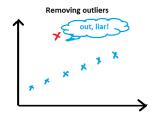
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- Missing call rate is not only a measure of data completeness, but is also a measure of genotype quality







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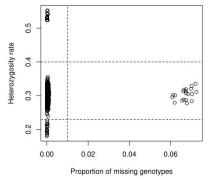
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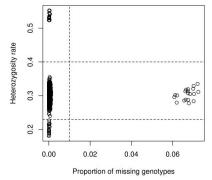
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- Outlying population ancestry
 - ► confounding due to population structure



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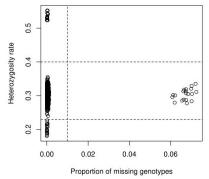
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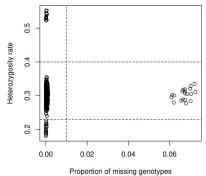


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- ullet Dashed lines denote QC thresholds (exclude samples with missing call rate > 0.1, and samples with heterozygosity rate < 0.23 and > 0.4)

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- Dashed lines denote QC thresholds (exclude samples with missing call rate > 0.1, and samples with heterozygosity rate < 0.23 and > 0.4)
- Rule of thumb: remove individuals who deviate \pm 3 SD from the samples' heterozygosity rate mean

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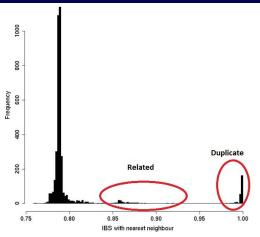
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- Common to plot histogram of IBS of each individual with "nearest neighbour"



IBS Distribution



- For each individual, the distance to its nearest neighbour is calculated
- Remove one sample from each duplicate or related pair (usually one with lowest call rate)
- Alternative: take account of relatedness in analysis
- The absolute amount of IBS sharing depends on allele frequencies in the population
- Methods that estimate kinship or relatedness coefficients typically aim for estimating identity-by-descent (IBD)

• The degree of recent shared ancestry for a pair of individuals



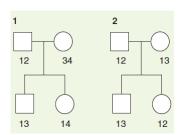
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- Pedigree 1: Siblings share allele 1 IBD (inherited from the father)
- Pedigree 2: Siblings share allele 1 IBS (inherited from different parents)

Forabosco et al. Expert Rev. Mol. Diagn. 5(5), (2005). doi: 10.1586/14737159.5.5.781

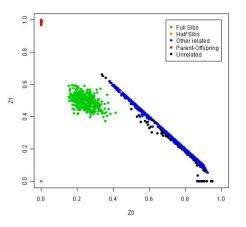
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 - ullet in practice, use $\hat{\pi}>0.98$
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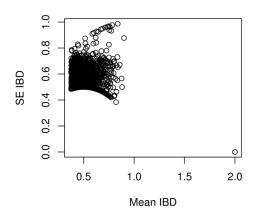
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- Prune the data for LD before assessing IBD
 - shared region of high LD results in more shared variants than one of low LD, even if the two regions are the same size



IBD Plot

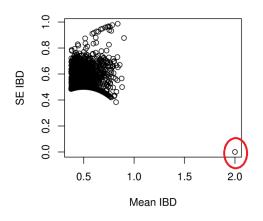
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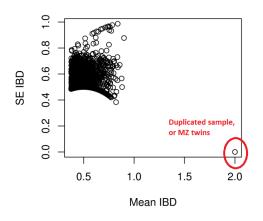


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MZ twins



Duplicated samples



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Cryptic relatedness

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MZ twins Duplicated samples DZ twins Cryptic relatedness

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- Including related individuals in the analysis, without accounting for these relationships, can increase false positive error rates and reduce power
- Mixed modelling approaches account for "relatedness" between individuals (families, cryptic relatedness, population structure) by allowing for kinship

Gender Check - X Chromosome



 Calculate the homozygosity rate F across all X-chromosome SNPs for each individual in the sample and compare these to the expected rate



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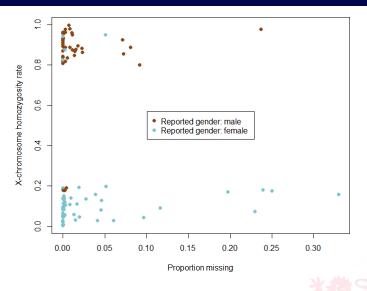
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- Gender error reported for mismatch in reported and genetic sex
- Discrepancies with external gender information may reflect:
 - errors in external data
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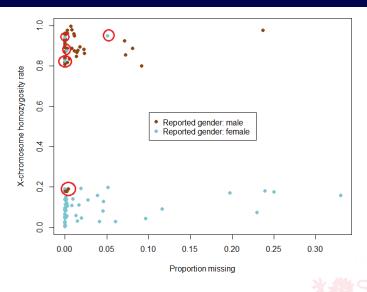


Gender Check - Plot



Spot the discrepancies...

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Gender Check - Examples

| Reported | Homozygosity | Gender according |
|----------|--------------|------------------|
| gender | rate | to SNPs |
| Male | 0.98 | Male |
| Female | 0.03 | Female |
| Female | 0.99 | Male |
| Female | 0.28 | Unknown* |
| Female | 0.35 | Unknown** |

^{*} Likely a female with sex chromosome anomaly (e.g. XX/XO mosaic, loss-of-heterozygosity on X)

Adapted from Turner et al. Curr Protoc Hum Genet (2011). doi:10.1002/0471142905.hg0119s68



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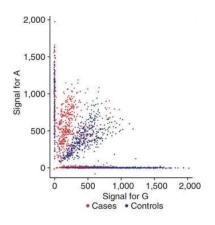


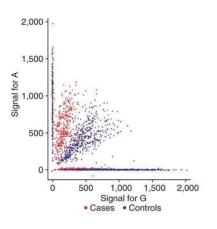
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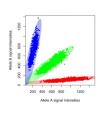


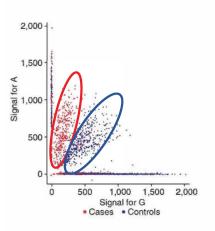
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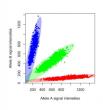
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- Extreme differential call rates between cases and controls

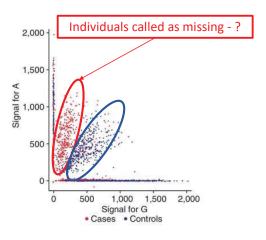


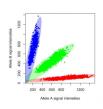


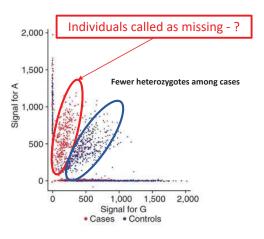


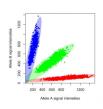














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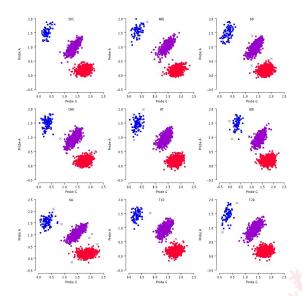




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- PLINK: whole-genome association analysis toolset
 - ▶ Spoiler alert: PLINK will be used in practicals

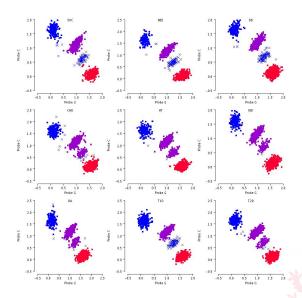


Visual Inspection of Cluster Plots - Good SNP



The Wellcome Trust Case Control Consortium. Nature (2007). doi:10.1038/nature05911

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Summary



- QC is an essential step of the analysis
- QC criteria are subjective and vary from one study to another
- Sample QC filters should not be so stringent as to remove the majority of the analysis cohort
- SNP QC filters should eliminate the worst quality markers
- All SNPs demonstrating evidence for association should be followed up with visual inspection of cluster plots