

4. Model fitting

Thomas Lumley Ken Rice

Universities of Washington and Auckland

Liège, September 2011

Regression commands

Two of the most important R commands;

• lm(): fits Linear Models

• glm(): fits **G**eneralized **L**inear **M**odels

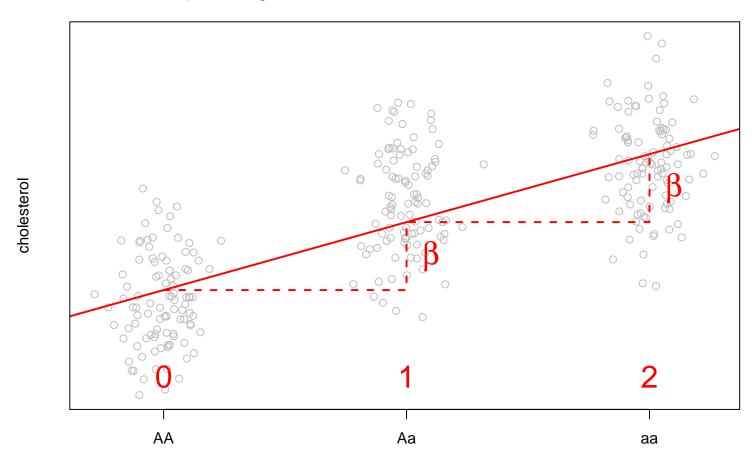
(If you've used SAS, its glm is **not** the same as R's)

'Linear Regression' and 'Logistic Regression' are special cases.

There's a lot to learn here — entire graduate courses! — so the help files are huge. How are lm(), glm() used in genetics?

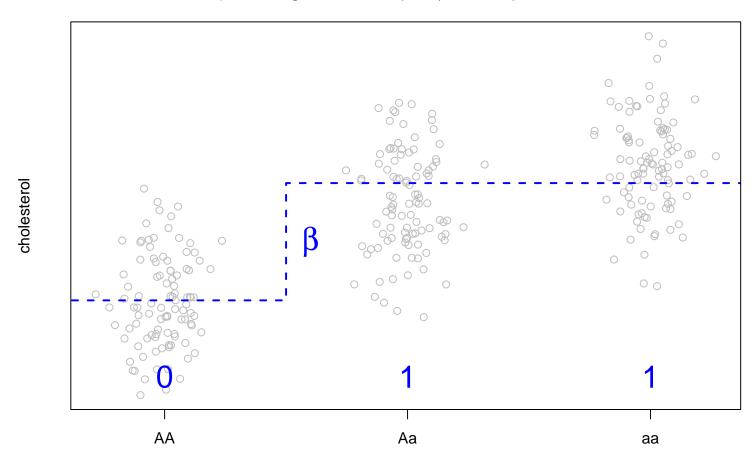
Many analyses fit the 'additive model'

$$y = \beta_0 + \beta \times \#$$
minor alleles



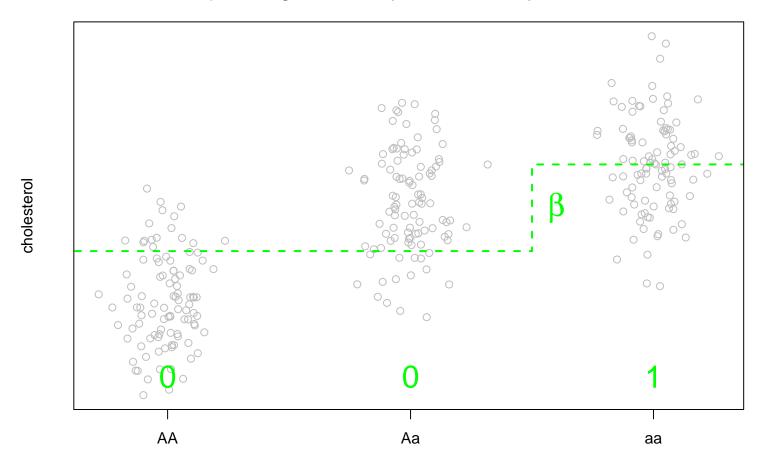
An alternative is the 'dominant model';

$$y = \beta_0 + \beta \times (G \neq AA)$$



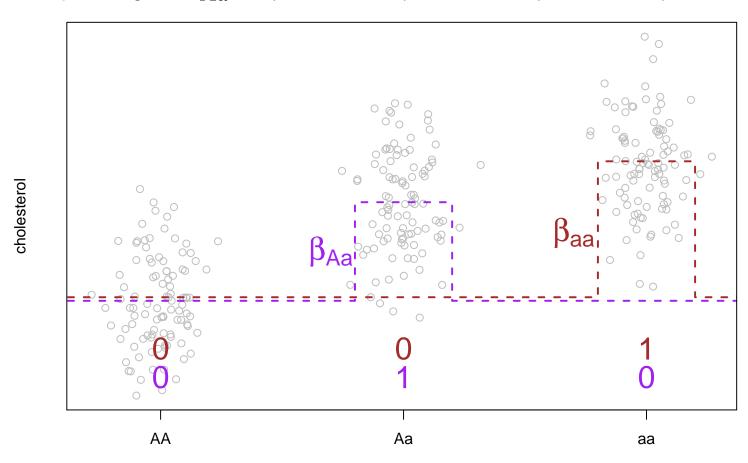
or the 'recessive model';

$$y = \beta_0 + \beta \times (G == AA)$$



Finally, the 'two degrees of freedom model';

$$y = \beta_0 + \beta_{Aa} \times (G == Aa) + \beta_{aa} \times (G == aa)$$



The lm() command fits all of these, in the same way. Formally,

```
{\tt lm}({\tt outcome} \sim {\tt genetic.predictor}, {\tt [...]})
```

estimates the association between outcome and predictor

The **optional** arguments [...] might be

- data = my.data your dataset
- subset = race=="CEPH" use partial data
- weights = − for advanced analyses

How to make the genetic.predictor variable? Suppose you had genotypes stored as character strings ("AA"/"Aa"/"aa") in a vector g. You might use these commands;

Chosen Model	Command to define variable		
Additive	genetic.predictor <- (g=="Aa") + 2*(g=="aa")		
Dominant	<pre>genetic.predictor <- (g=="Aa") (g=="aa")</pre>		
Recessive	genetic.predictor <- g=="aa"		
2 degs of freedom	<pre>genetic.predictor <- factor(g)</pre>		

When R meets FALSE or TRUE in a 'math' setting, it will **coerce** them to be zero or one. So 1 + 2*TRUE is 3, TRUE + 2*FALSE is 1, etc. Using factor() sets up several binary variables

- There are many other ways to do this!
 Use table(g, genetic.predictor) to check your method
- Often, genotypes may be stored as 0/1/2. This is easier to work with in R – but makes it harder to decide if A/C/G/T is the minor allele, or risk allele.

lm(): Estimates, Intervals, p-values

lm() produces point estimates for your model;

also available via my.lm\$coefficients or coef(my.lm).

The coefficients in the output tell you the **additive increase** in outcome associated with a **one-unit** difference in the genetic predictor.

The coefficient for predictor is in units of cholesterol per 'a' allele

lm(): Estimates, Intervals, p-values

You will also want **confidence intervals**;

Remember to **round these numbers** to an appropriate number of significant figures! (2 or 3 is usually enough)

We are **seldom** interested in the Intercept

lm(): Estimates, Intervals, p-values

Two-sided **p-values** are also available;

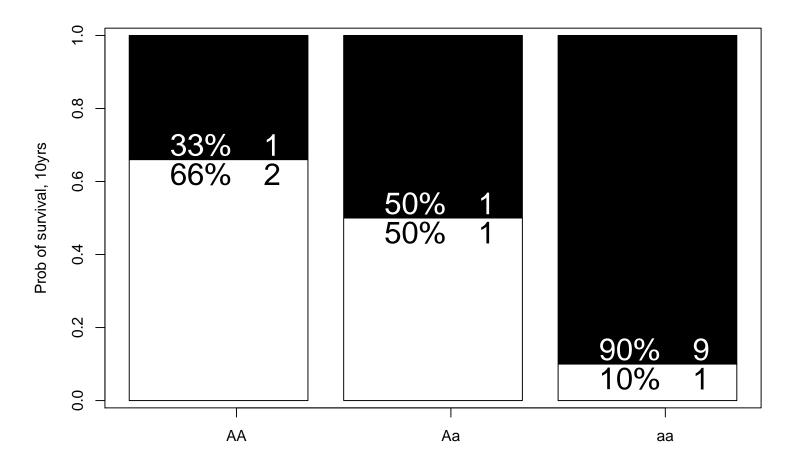
- In this data, we have **strong evidence** of an **additive effect** of the minor allele on cholesterol
- summary(my.lm) gives many other details ignore for now
- ullet Confidence intervals are just Estimate $\pm 2 \times \text{Std.Error}$

Logistic regression is the 'default' analysis for binary outcomes

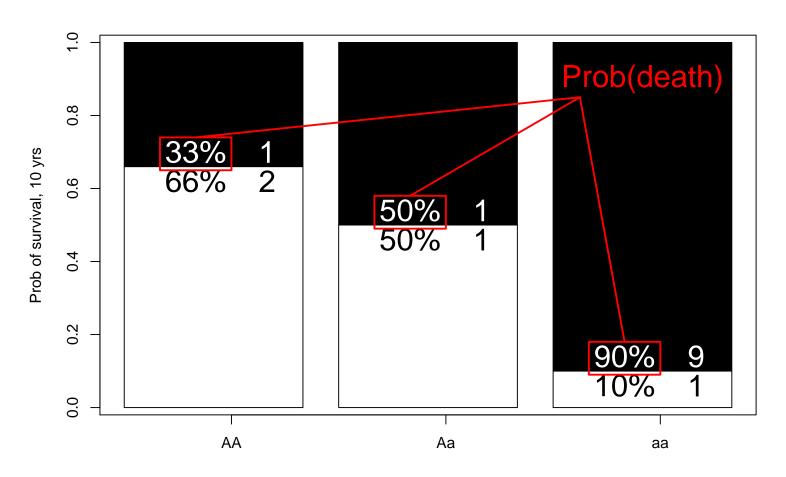
Outcome	Туре	Regression	Scale
Cholesterol			
Blood Pressure	Continuous	Linear	Difference in Outcome
BMI			
Death			
Stroke	Binary	Logistic	Ratio of odds
BMI>30			

What are **odds**? Really just **probability**...

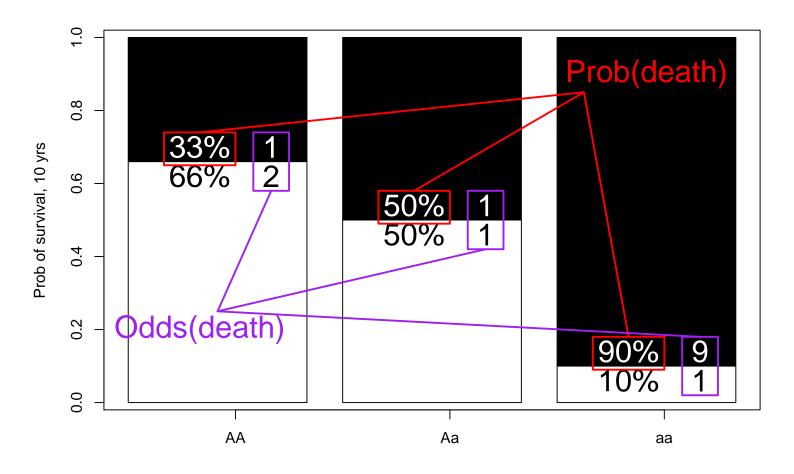
Odds are a [gambling-friendly] measure of chance;



Odds are a [gambling-friendly] measure of chance;



Odds are a [gambling-friendly] measure of chance;



– so what are odds ratios?

Using the data from slide 4.12;

```
> genpred2 <- factor(g) # the 2df model
> glm1 <- glm( dead10yrs ~ genpred2, family=binomial)
> coef(glm1)
    pred2Aa     pred2aa
    0.6931    2.8904
```

- These are \log odds ratio estimates; to transform to OR, use $e^{0.6931}=2, e^{2.8904}=18$
- They are given relative to the baseline group 'AA' in this case
- Don't forget the family=binomial argument!

Confidence intervals, p-values as with lm(), for the log odds ratios;

Use exp() to get odds ratio estimates, intervals; p-values are scale-independent

The formula syntax

We saw $lm(y\sim genetic.predictor)$ and $glm(y\sim genpred2)$. To see how phenotype depends on *several* covariates, we specify e.g.

y
$$\sim$$
 genotype.pred + age + sex

- formally, this gives *multivariate regression*; the genotype.pred coefficients reflect the genotype effects *adjusted for age and sex*
 - Separate covariates with '+'. This is not addition!
 - For now, make predictor variables first, then do regression.
 It's possible to do everything in one step, but use of e.g. '+' will confuse R unless you're careful.
 - For keen people; in the formula syntax, * indicates that interactions should be fitted, I() insulates mathematical operations, -1 removes the intercept... see ?formula
 - For *very* keen people; vcovHC() in the sandwich package provides 'robust' standard errors; coeftest() in the lmtest package can use them to give 'robust' tests.