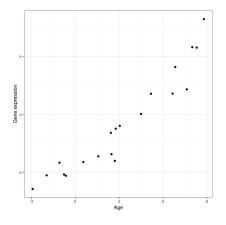
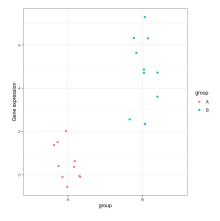
# Regression with many features

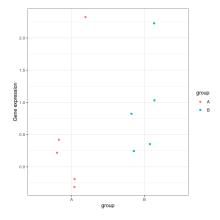
#### A scatter plot of age and a feature of interest.



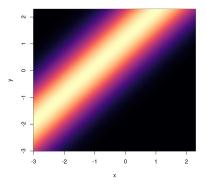
#### A scatter plot of a grouping and a feature of interest.



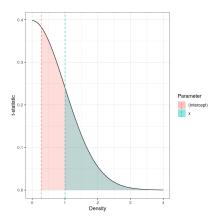
#### A scatter plot of a grouping and a feature of interest.



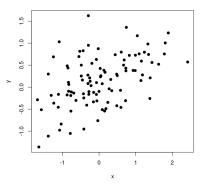
Regression is like a normal distribution with varying mean.



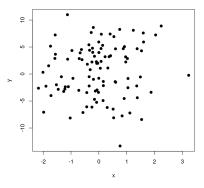
The p-value for a regression coefficient represents how often it'd be observed under the null.



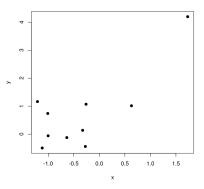
Relationships can be significant with small noise and small effects.



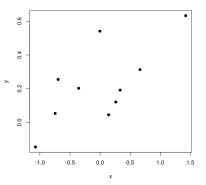
Relationships can be non-significant with large noise and large effects.



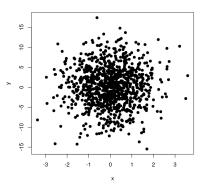
With few points, relationships can be non-significant with large noise and large effects.



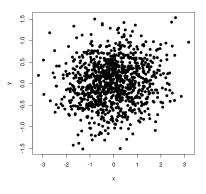
With few points, relationships can be significant with small noise and small effects.



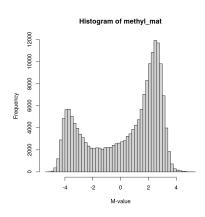
### With many points, relationships can be significant with large noise and small effects.



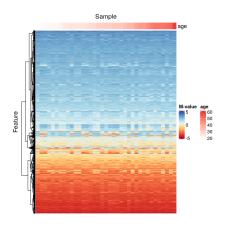
With many points, relationships can be significant with small noise and tiny effects.



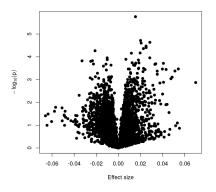
#### Methylation levels are generally bimodally distributed.



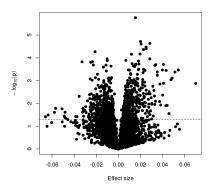
Visualising the data as a heatmap, it's clear that there's too many models to fit 'by hand'.



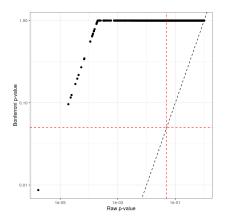
Plotting significance against effect size, it's clear that the two are related (but not 1-1).



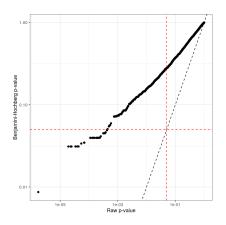
## Plotting p-values against effect sizes for a randomised outcome shows we still observe 'significant' results.



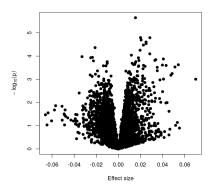
## Bonferroni correction often produces very large p-values, especially with low sample sizes.



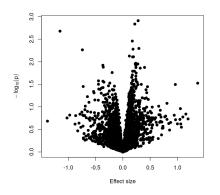
### Benjamini-Hochberg correction is less conservative than Bonferroni



Plotting p-values against effect sizes using limma; the results are similar to a standard linear model.



A plot of significance against effect size for a regression of smoking against methylation.



#### Caption

