

Differential expression analysis of microarray experiments

Bioconductor 2007

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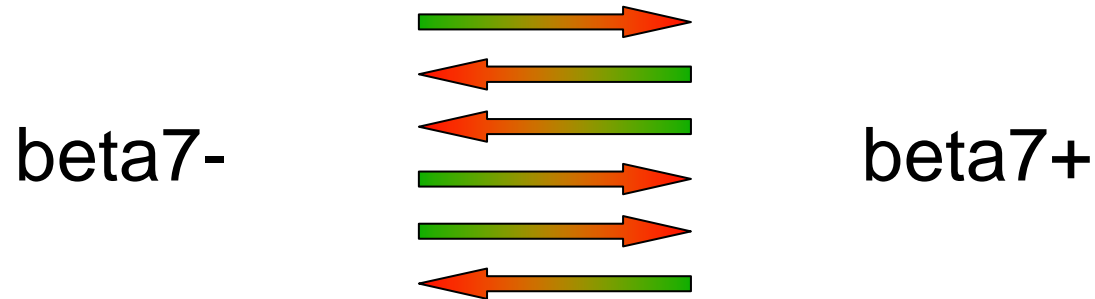
Getting started

- Copy the directory 'bioc2007limma' from the flashdisk to a convenient place on your computer, e.g., c:/bioc2007limma
- Open c:/bioc2007limma/html/index.html in your browser
- Make c:/bioc2007limma/data the working directory of your R session

limma package documentation

- Function help pages
- Class help pages
- Group help pages
- User's Guide

Example 1: Integrin beta7+ vs beta7-

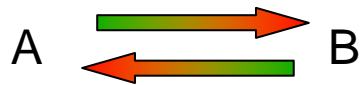


- Reading two-color data
- Control spots
- Background correction
- Dye-swaps
- Empirical Bayes differential expression

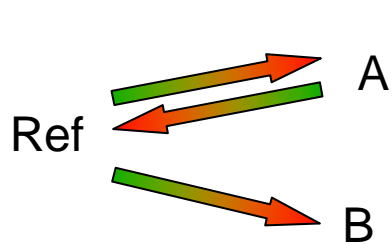
Designs \rightarrow Linear Models



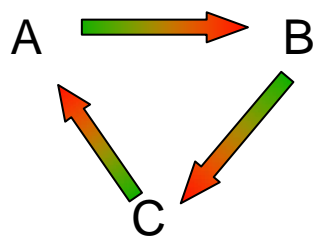
$$y = \log_2(R/G) \equiv B - A$$



$$\begin{pmatrix} y_1 \\ y_2 \end{pmatrix} = \begin{pmatrix} 1 \\ -1 \end{pmatrix} \beta \quad \beta \equiv B - A$$



$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -1 & 0 \\ 1 & 1 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} \quad \begin{aligned} \beta_1 &\equiv A - \text{Ref} \\ \beta_2 &\equiv B - A \end{aligned}$$



$$\begin{pmatrix} y_1 \\ y_2 \\ y_3 \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ -1 & 1 \\ 0 & -1 \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \end{pmatrix} \quad \begin{aligned} \beta_1 &\equiv B - A \\ \beta_2 &\equiv C - A \end{aligned}$$

Linear Model Estimates

Obtain a linear model for each gene g

$$E(\mathbf{y}_{\hat{g}}) = X \mathbf{b}_{\hat{g}}$$

$$\text{var}(\mathbf{y}_{\hat{g}}) = W_g^{-1} s_g^2$$

Estimate models to get

coefficients

$$\hat{b}_{gj}$$

standard deviations

$$s_g$$

standard errors

$$\text{se}(\hat{b}_{gj})^2 = c_{gj} s_g^2$$

Hierarchical model for variances

Data

$$s_g^2 \sim s_g^2 \frac{c_{d_g}^2}{d_g}$$

Prior

$$\frac{1}{s_g^2} \sim s_0^2 \frac{c_{d_0}^2}{d_0}$$

Posterior

$$E \left[\frac{1}{s_g^2} \mid s_g^2 \right] = \frac{d_0 + d_g}{s_0^2 d_0 + s_g^2 d_g}$$

Posterior Statistics

Posterior variance estimators

$$s_g^2 = \frac{s_0^2 d_0 + s_g^2 d_g}{d_0 + d_g}$$

Moderated t-statistics

$$t_{gj} = \frac{\hat{b}_{gj}}{s_g \sqrt{c_{gj}}}$$

Exact distribution for moderated t

An unexpected piece of mathematics shows that, under the null hypothesis,

$$t_g^0 : t_{d_0 + d_g}$$

The degrees of freedom add!

The Bayes prior in effect adds d_0 extra arrays for estimating the variance.

Hierarchical model for means

Data $\hat{b}_{gj} : N(b_{gj}, c_{gj} s_g^2)$

Prior $P(b_{gj} = 0) = p$

$$b_{gj} | b_{gj} = 0 : N(0, c_{0j} s_g^2)$$

Posterior Odds

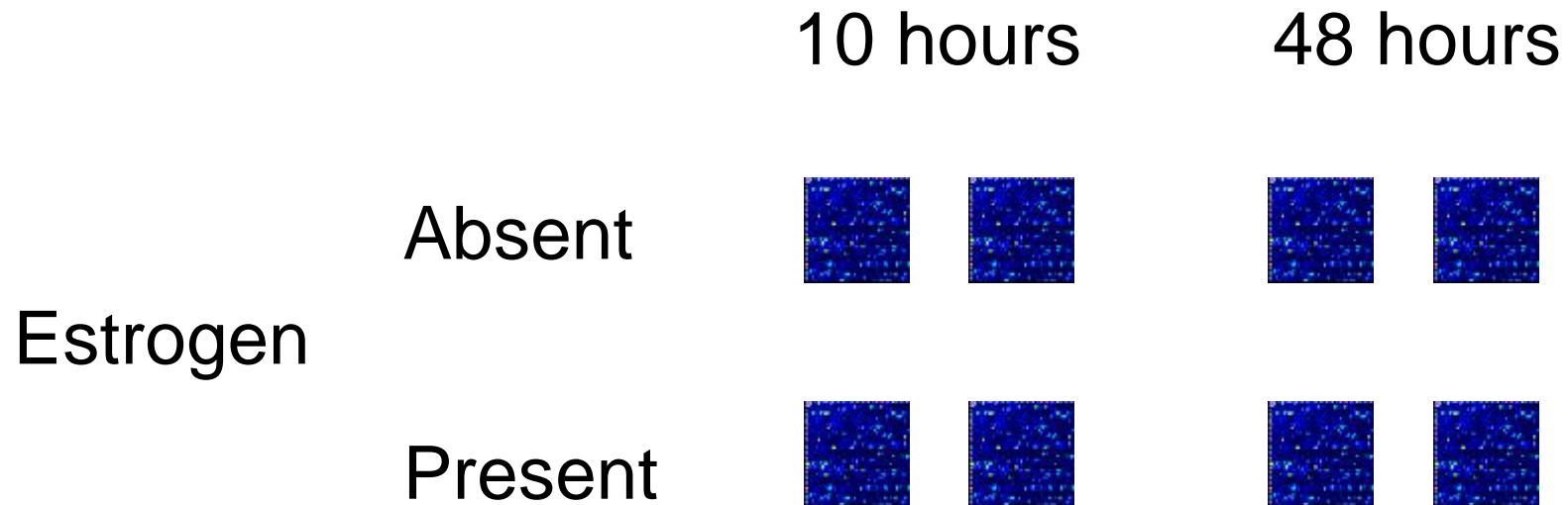
Posterior odds of differential expression

$$\frac{p(b = 1 \mid \hat{b}, s^2)}{p(b = 0 \mid \hat{b}, s^2)} = \frac{p \frac{c}{c + c_0} \frac{1}{\sigma^2} \left(\frac{1 + d + d_0}{2} \right)}{1 - p \frac{c}{c + c_0} \frac{1}{\sigma^2} \left(\frac{c}{c + c_0} + d + d_0 \right)}$$

Monotonic function of $|\tilde{t}|$

Hence \tilde{t} gives the **best possible ranking** of genes

Example 2: Estrogen



- Reading Affymetrix data
- Factorial designs
- Gene set tests

Gene sets

- Test significance of a (prior specified) group of genes
- The genes might belong to a known pathway or might be the top genes from a related experiment
- The set might be significant even if individual genes are not
- Gene set enrichment analysis (GSEA) originated by Mootha et al PNAS 2003 and Subramanian et al PNAS 2005

Mean rank gene set tests

A priori subset
of genes

All microarray probes,
ranked by a **test
statistic** of interest

$X_1, X_2, X_3 \dots X_n$

t1
t2
t3
t4
:

Look for **ranks** for set genes amongst test statistics

Example 3:
Targets of SAHA and depsipeptide

Case Study

Peart, Smyth, van Laar, Richon,
Holloway, Johnstone

Identification and functional significance
of genes regulated by structurally diverse
histone deacetylase inhibitors

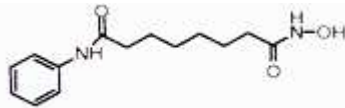
PNAS Feb 2005

Tumour cell growth inhibitors

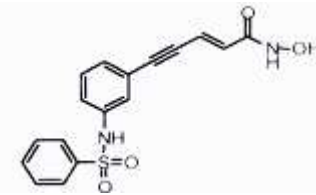
- Histone deacetylase inhibitors (HDACis) are **anti-cancer agents** that inhibit tumour cell growth and survival
- **Not toxic** to normal cells
- Genes active in biological effects are **unknown**



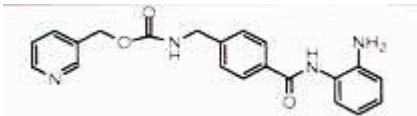
butyrate



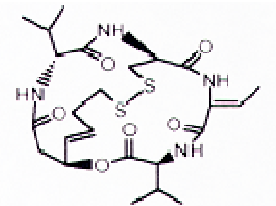
SAHA



oxamflatin



MS-27-275

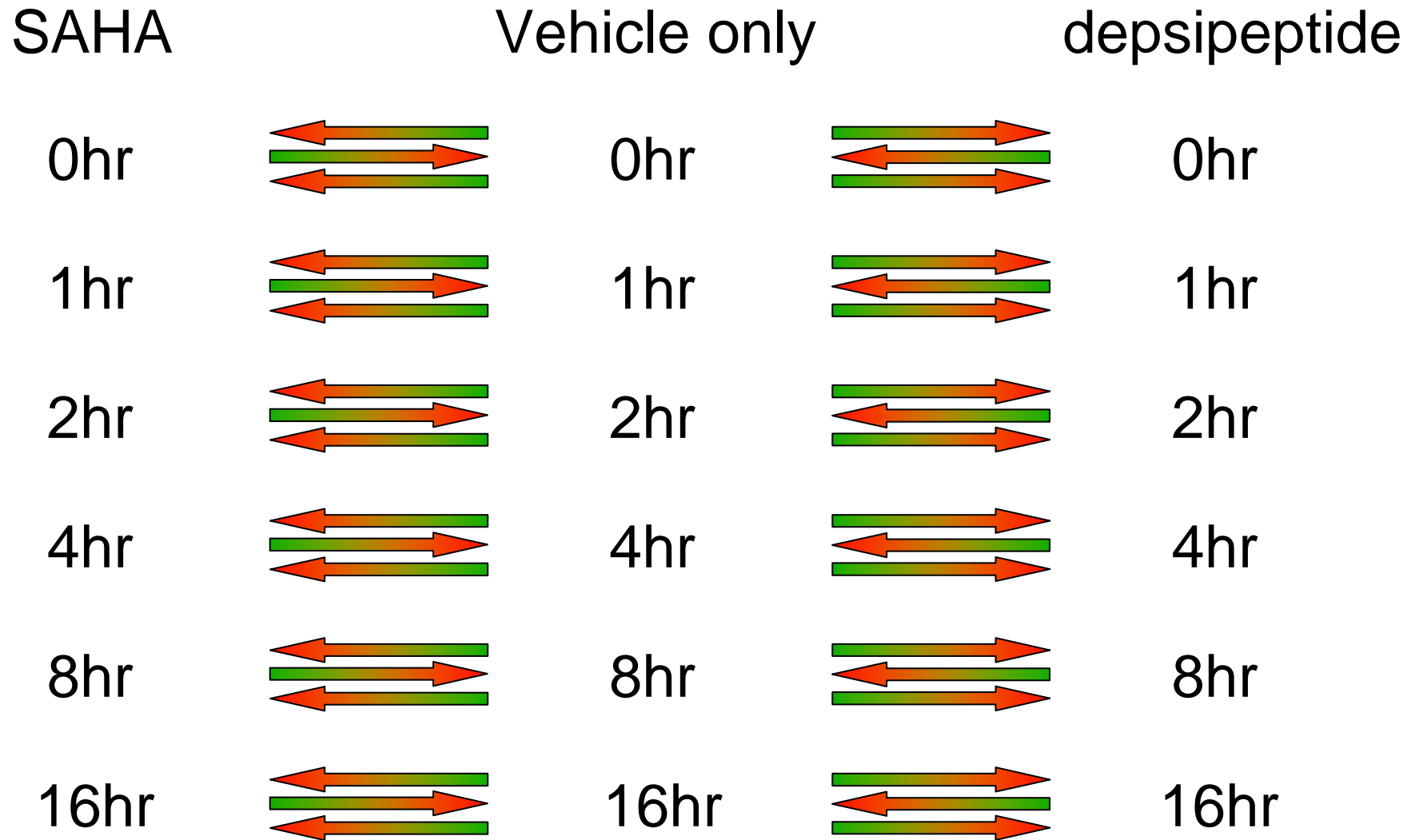


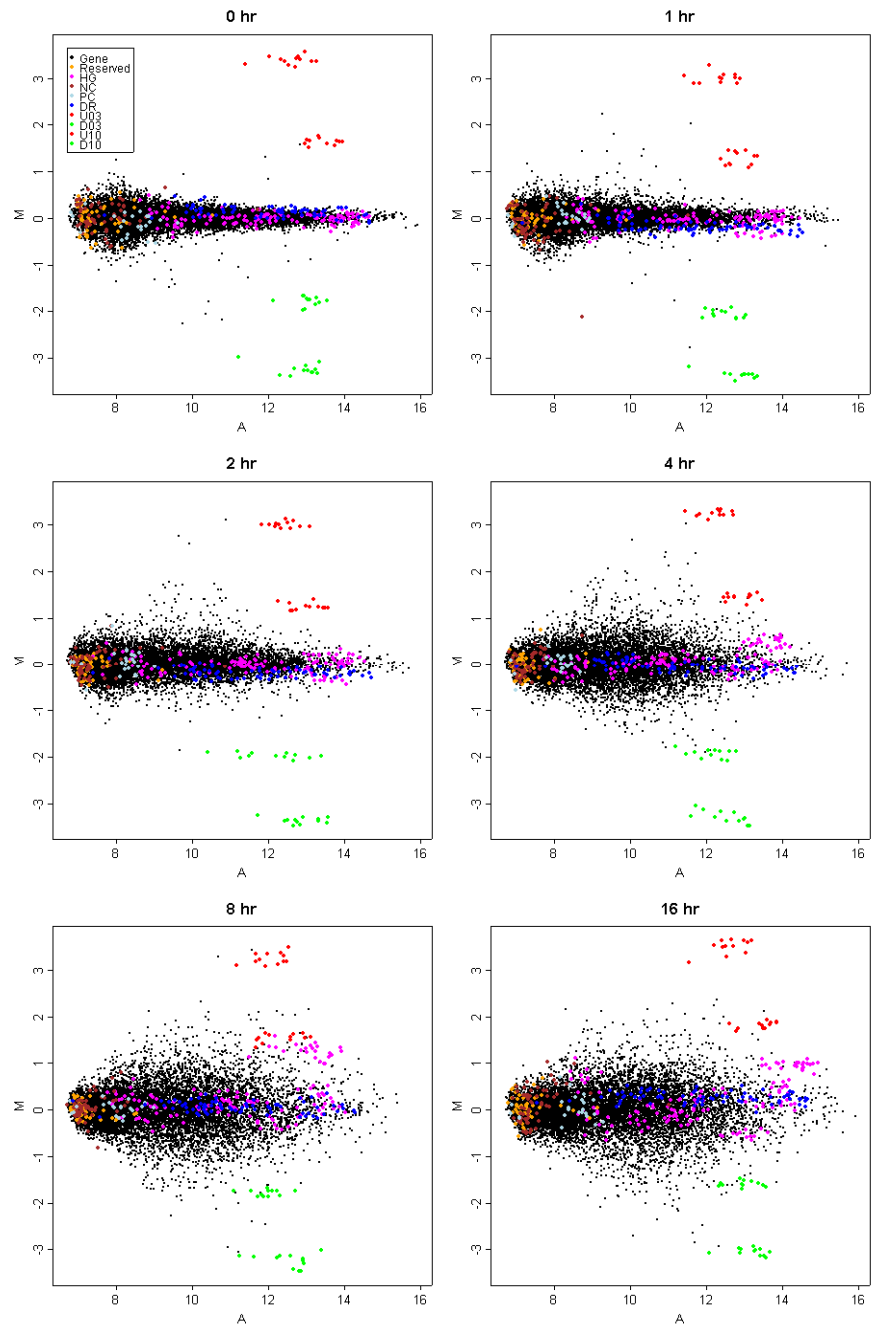
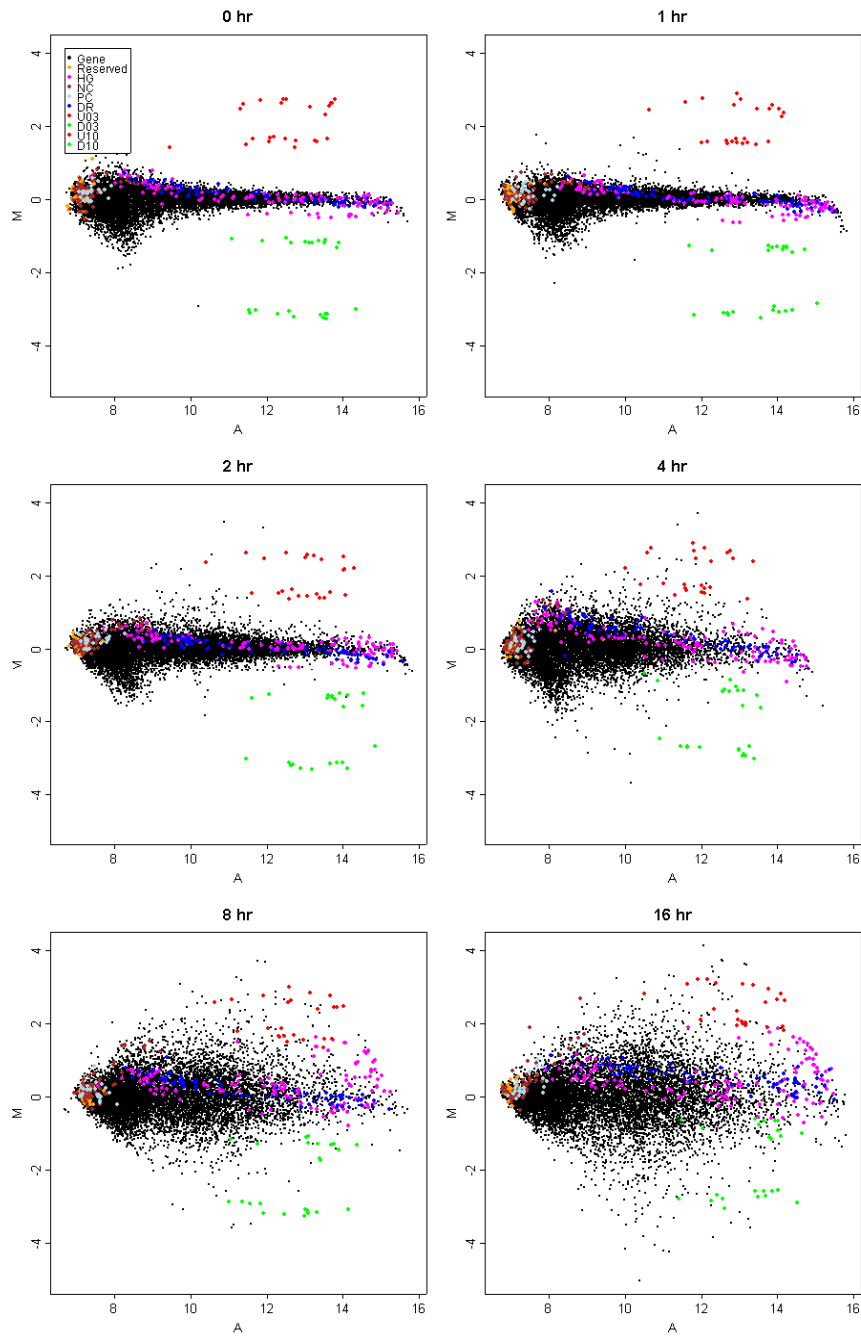
depsipeptide

Target cell cultures

- Study effects of SAHA and depsipeptide on the acute T-cell leukemia cell line **CEM**
- **SAHA** and **depsipeptide** are structurally different but have similar biological effects (induce death through intrinsic apoptotic pathway)
- Prising out subtle differences is of great interest

Experimental design





Aims of experiment

- Identify **common responders**: genes which respond similarly to SAHA and depsipeptide
- Identify **specific responders**: genes which respond to one of SAHA or depsipeptide, but not to the other
- **Different responders**, genes which respond to both SAHA and depsipeptide but differently, are of lesser interest

Classic ANOVA methods are applicable

- An F-test for time on 5 df will find genes which change **at any time** (simpler than a series of t-tests at each time)
- An F-test for drug x time **interaction** will find genes which react **differently** to the two drugs

Moderated F-Statistic

The idea of shrinking the variance extends immediately to multiple contrasts

Moderated F-statistic

$$F_g^0 = \frac{\text{MST}_g}{S_g^0} : F_{k, d_g + d_0}$$

MST=Mean Sum of squares between Treatments

Linear model analysis

- Fit **linear model** to the M-values (log-ratios) for each gene
- Include effects for **drug x time**
- Allow for probe/drug specific **dye-effects**
- Treat each time series of 6 arrays as a **randomized block**, i.e., allow arrays hybridized together to be correlated

Classifying common and specific responders

Tests	Common	SAHA specific	depsi specific
Time (SAHA)	☺	☺	X
Time (depsi)	☺	X	☺
Drug x time interaction	X	☺	☺

☺ = significant, X = not significant

Acknowledgements

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- Andy Holloway