

# Analyzing One-Color Data with limma

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# Introduction

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Linear models

*t*-test

Weighting Chips

Higher-order Models

Batch Effects

## Assumptions

- Data are one-channel microarray data
  - Affymetrix
  - Nimblegen
  - Possibly cDNA chip with common reference
- We assume data have been normalized and summarized
- Goal is to make comparisons
  - *t*-tests
  - linear models

# limma package

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## Why limma?

- Pros
  - Highly flexible
  - Increased power
    - Empirical Bayes
    - Linear modeling
    - Chip weighting
- Cons
  - Complexity
    - Design matrices
    - Contrast matrices

# Simple Example

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## Compare two groups

$$t = \frac{\hat{x} - \hat{y}}{\frac{\hat{\sigma}}{\sqrt{N-1}}}$$

# Graphical Example

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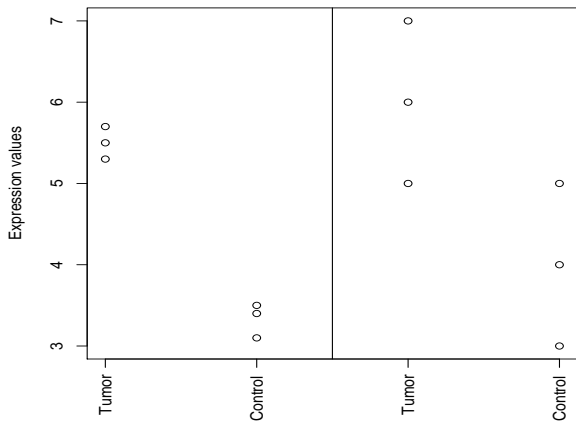
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# Graphics

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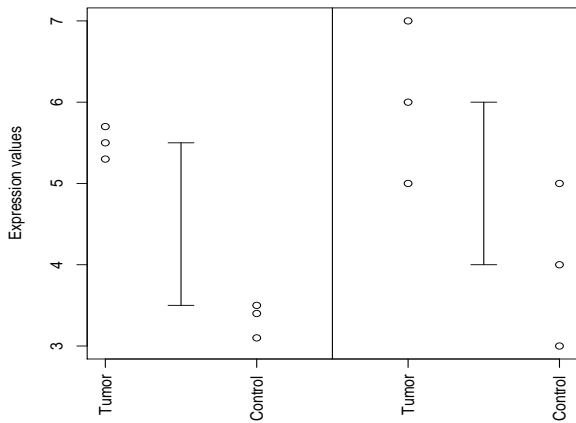
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# Graphics

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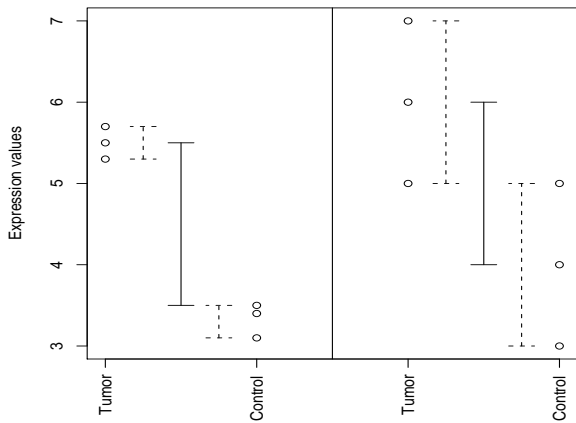
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# Design Matrix

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```
> samples
[1] Control Control Control Tumor   Tumor
[6] Tumor
Levels: Control Tumor
> design <- model.matrix(~0 + samples)
> colnames(design) <- levels(samples)
> design
      Control Tumor
1          1     0
2          1     0
3          1     0
4          0     1
5          0     1
6          0     1
attr(,"assign")
[1] 1 1
```



# Contrast Matrix

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## Numerator

```
> contrast <- makeContrasts(Tumor - Control,  
+                             levels = design)  
> contrast
```

	Contrasts
Levels	Tumor - Control
Control	-1
Tumor	1

# Empirical Bayes

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## Denominator

Remember 'standard'  $t$ -test:

$$t = \frac{\hat{x} - \hat{y}}{\frac{\hat{\sigma}}{\sqrt{N-1}}}$$

limma uses Empirical Bayes adjusted denominator:

$$t = \frac{\hat{x} - \hat{y}}{s + s_0}$$

$$s = \frac{\hat{\sigma}}{\sqrt{N-1}}$$

# Why adjust?

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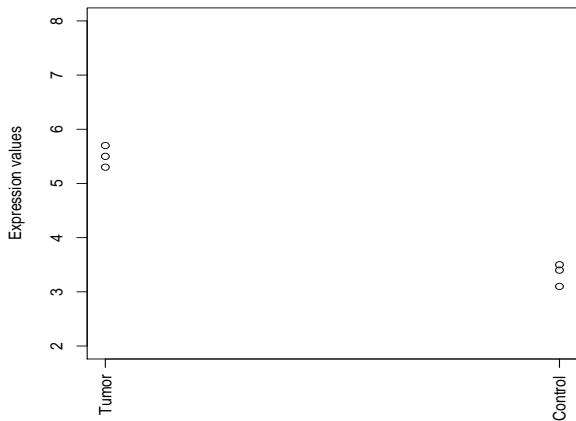
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# Why adjust?

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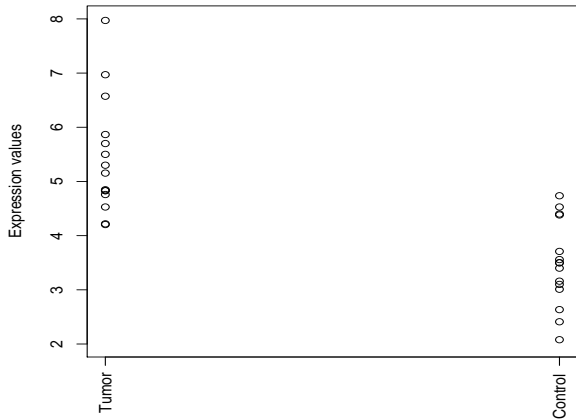
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# Why adjust?

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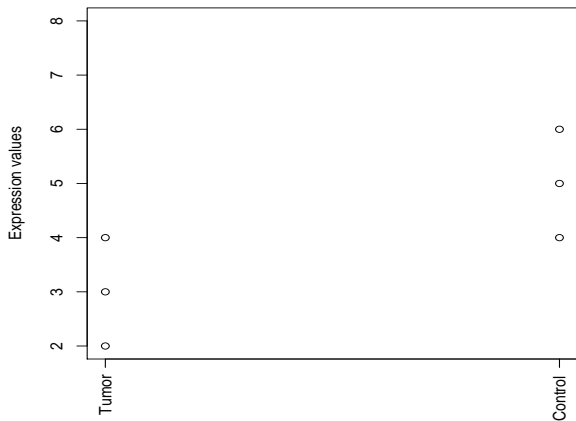
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# Why adjust?

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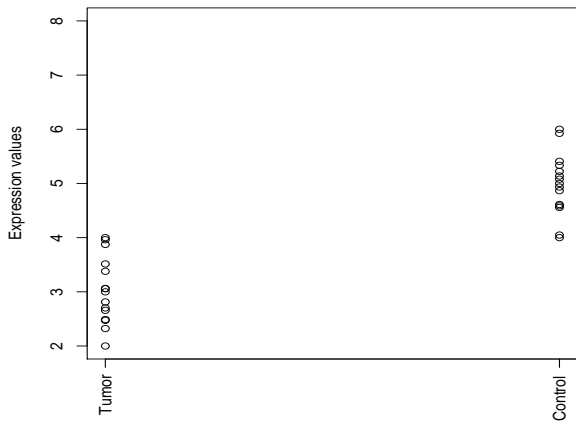
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# $t$ -test

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## Practice $t$ -test

Load affy and limma libraries

Attach sample.ExpressionSet dataset

Look at phenoData object associated

Do a  $t$ -test comparing the male and female samples

# t-test

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```
> library(affy)
> library(limma)
> data(sample.ExpressionSet)
> eset <- sample.ExpressionSet
> head(pData(eset))
```

	sex	type	score
A	Female	Control	0.75
B	Male	Case	0.40
C	Male	Control	0.73
D	Male	Case	0.42
E	Female	Case	0.93
F	Male	Control	0.22



# t-test

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```
> design <- model.matrix(~ 0 + pData(eset)[,1])
> colnames(design) <- levels(pData(eset)[,1])
> contrast <- makeContrasts(Male - Female,
+                           levels = design)
> fit <- lmFit(eset, design)
> fit2 <- contrasts.fit(fit, contrast)
> fit2 <- eBayes(fit2)
```

# t-test

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```
> head(topTable(fit2, coef = 1))
```

	ID	logFC	AveExpr	t
314	31553_at	-11.3	7.2	-2.8
98	31337_at	97.2	422.8	2.6
303	31542_at	9.4	13.0	2.5
310	31549_at	-7.1	19.6	-2.2
4	AFFX-MurFAS_at	-7.3	13.9	-2.2
149	31388_at	16.4	33.2	2.2

	P.Value	adj.P.Val	B
314	0.009	0.99	-4.6
98	0.016	0.99	-4.6
303	0.022	0.99	-4.6
310	0.036	0.99	-4.6
4	0.036	0.99	-4.6
149	0.040	0.99	-4.6

# Dealing with Outliers

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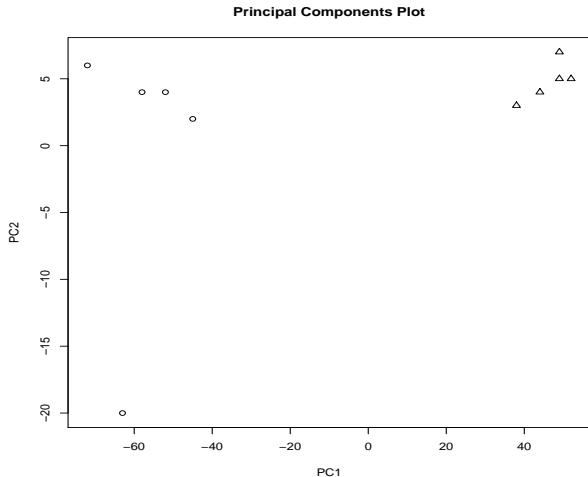
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# Array Weights

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```
> aw <- arrayWeights(eset, design)
> aw
      1      2      3      4      5      6      7      8      9
0.81 0.69 1.06 1.46 1.68 1.37 0.65 0.83 0.72
     10     11     12     13     14     15     16     17     18
0.83 1.04 2.58 0.82 0.84 1.43 1.11 0.99 0.73
     19     20     21     22     23     24     25     26
0.63 0.76 0.84 0.68 2.65 1.14 1.25 0.73

> fit <- lmFit(eset, design, weights = aw)
```

# Two-factor ANOVA

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sample.ExpressionSet Again

```
> head(pData(eset))
```

	sex	type	score
A	Female	Control	0.75
B	Male	Case	0.40
C	Male	Control	0.73
D	Male	Case	0.42
E	Female	Case	0.93
F	Male	Control	0.22

# Design Matrix

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```
> sex <- pData(eset)[,1]
> type <- pData(eset)[,2]
> design <- model.matrix(~ 0 + sex:type)
> colnames(design) <- c("Fem.Case", "Male.Case",
+                       "Fem.Contr", "Male.Contr")
> head(design)
```

	Fem.Case	Male.Case	Fem.Contr	Male.Contr
1	0	0	1	0
2	0	1	0	0
3	0	0	0	1
4	0	1	0	0
5	1	0	0	0
6	0	0	0	1

# Comparisons

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## What comparisons can we make?

- Male vs Female
- Case vs Control
- Case vs Control within sex
- Interaction

# t-test

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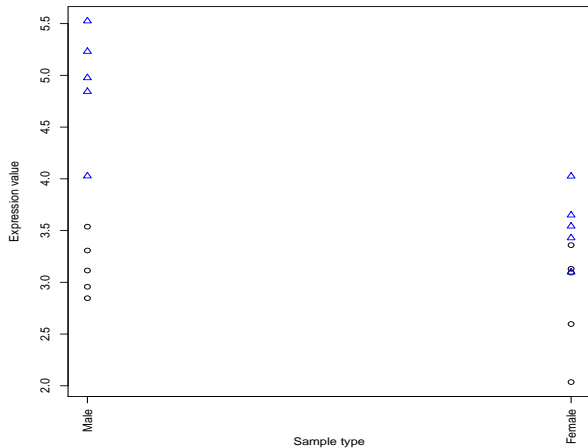
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# ANOVA

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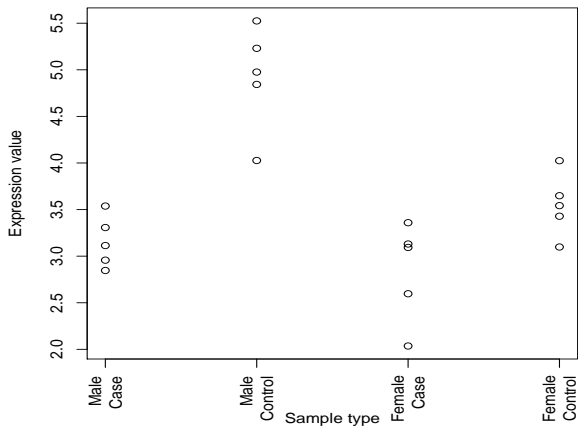
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# Practice ANOVA

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## Can you do the following?

- Compare Female Cases vs Female Controls
- Compare Female Cases vs Male Cases

# Create Contrasts Matrices

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```
> contrast <- makeContrasts(Fem.Case - Fem.Contr,  
+                           Fem.Case - Male.Case,  
+                           levels = design)  
> contrast
```

Contrasts

Levels	Fem.Case - Fem.Contr
Fem.Case	1
Male.Case	0
Fem.Contr	-1
Male.Contr	0

Contrasts

Levels	Fem.Case - Male.Case
Fem.Case	1
Male.Case	-1
Fem.Contr	0
Male.Contr	0

# Fit Model and Compute Contrasts

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Batch Effects

```
> fit <- lmFit(eset, design)
> fit2 <- contrasts.fit(fit, contrast)
> fit2 <- eBayes(fit2)
```

# Female Cases vs Controls

Bioconductor

```
> head(topTable(fit2, coef = 1))
```

	ID	logFC	AveExpr	t	P.Value
180	31419_r_at	-395	1447	-2.8	0.010
392	31631_f_at	27	-33	2.7	0.012
113	31352_at	-27	40	-2.7	0.013
374	31613_at	-44	77	-2.6	0.016
358	31597_r_at	-335	1634	-2.5	0.022
157	31396_r_at	-525	2504	-2.4	0.026

adj.P.Val B

180	0.75	-4.6
392	0.75	-4.6
113	0.75	-4.6
374	0.75	-4.6
358	0.75	-4.6
157	0.75	-4.6

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# Female Cases vs Male Cases

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```
> head(topTable(fit2, coef = 2))
```

	ID	logFC	AveExpr
314	31553_at	17.2	7.2
382	31621_s_at	-142.8	516.6
206	31445_at	-63.5	134.8
120	31359_at	11.7	11.9
43	AFFX-HUMRGE/M10098_5_at	-53.0	15.0
79	31318_at	-9.7	12.7

	t	P.Value	adj.P.Val	B
314	3.6	0.0016	0.49	-4.4
382	-3.5	0.0020	0.49	-4.4
206	-2.9	0.0075	0.93	-4.5
120	2.5	0.0209	0.93	-4.5
43	-2.5	0.0217	0.93	-4.5
79	-2.4	0.0235	0.93	-4.5

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# Interaction

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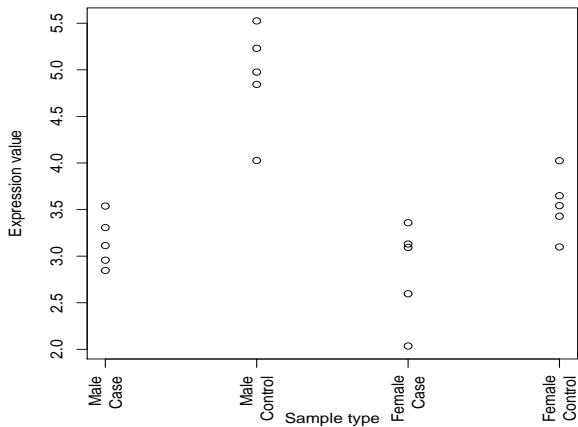
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# Interaction

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Batch Effects

$$\text{interaction} = (\text{FemCase} - \text{FemContr}) - (\text{MaleCase} - \text{MaleContr})$$

Set up contrasts the same way:

```
> contrast <- makeContrasts((Fem.Case - Fem.Contr) -  
+ (Male.Case - Male.Contr),  
+ levels = design)  
> colnames(contrast) <- "Interaction"  
> contrast
```

Levels	Contrasts Interaction
Fem.Case	1
Male.Case	-1
Fem.Contr	-1
Male.Contr	1



# Batch Effects

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Batch Effects

- Batch effects can arise from
  - Pairing
  - Experiments run at different times
  - Different reagents
- Watch out for
  - Aliasing
  - Creating batches unnecessarily
  - Assuming batch effect when there isn't one

# Pairing

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Batch Effects

- Mice first sampled as control then tumor introduced and re-sampled
- Wild type and mutant mice selected from several litters
- Several different cell lines treated similarly

# Example Batch Effect

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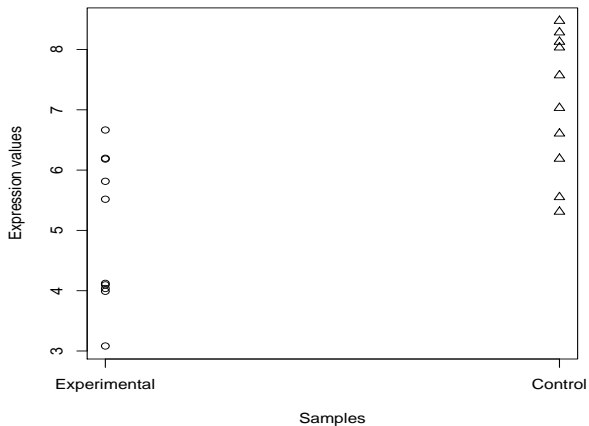
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# Example Batch Effect

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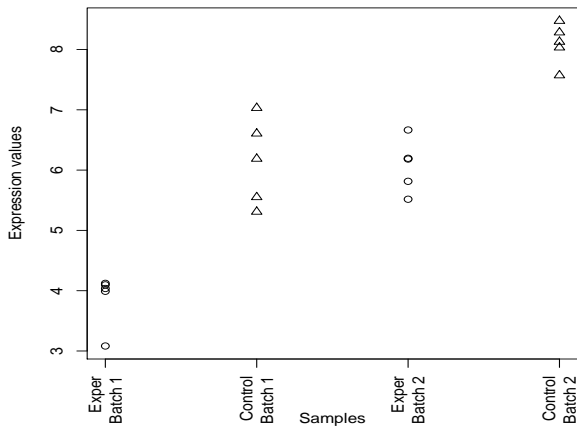
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# Controlling for Batch

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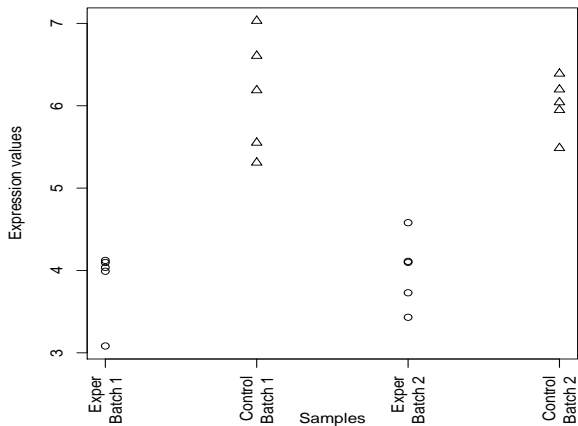
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**Batch Effects**



# Fitting a Batch Effect

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```
> treatment <- factor(rep(1:2, each = 12))
```

```
> treatment
```

```
[1] 1 1 1 1 1 1 1 1 1 1 1 1 2 2 2 2 2 2 2 2
```

```
[21] 2 2 2 2
```

```
Levels: 1 2
```

```
> batch <- factor(rep(1:2, each = 6, times = 2))
```

```
> batch
```

```
[1] 1 1 1 1 1 1 2 2 2 2 2 2 1 1 1 1 1 1 2 2
```

```
[21] 2 2 2 2
```

```
Levels: 1 2
```

# Fitting a Batch Effect

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```
> design <- model.matrix(~ 0 + treatment + batch)
> head(design)
```

	treatment1	treatment2	batch2
1	1	0	0
2	1	0	0
3	1	0	0
4	1	0	0
5	1	0	0
6	1	0	0

# Multiple Comparisons

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Setup:

We have compared two different drugs vs control  
and want to select significant genes

- `decideTests()`
  - `separate`
  - `global`
  - `hierarchical`
  - `nestedF`



# Venn Diagram

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```
> rslt <- decideTests(fit2, method = "nestedF")  
> vc <- vennCounts(rslt)  
> vennDiagram(vc)
```

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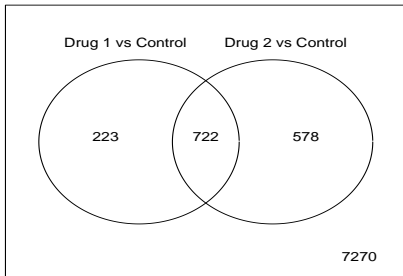
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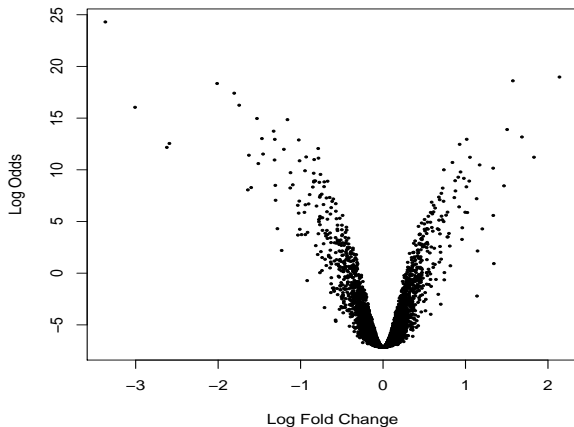
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# Volcano Plot

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```
> volcanoplot(fit2)
```



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