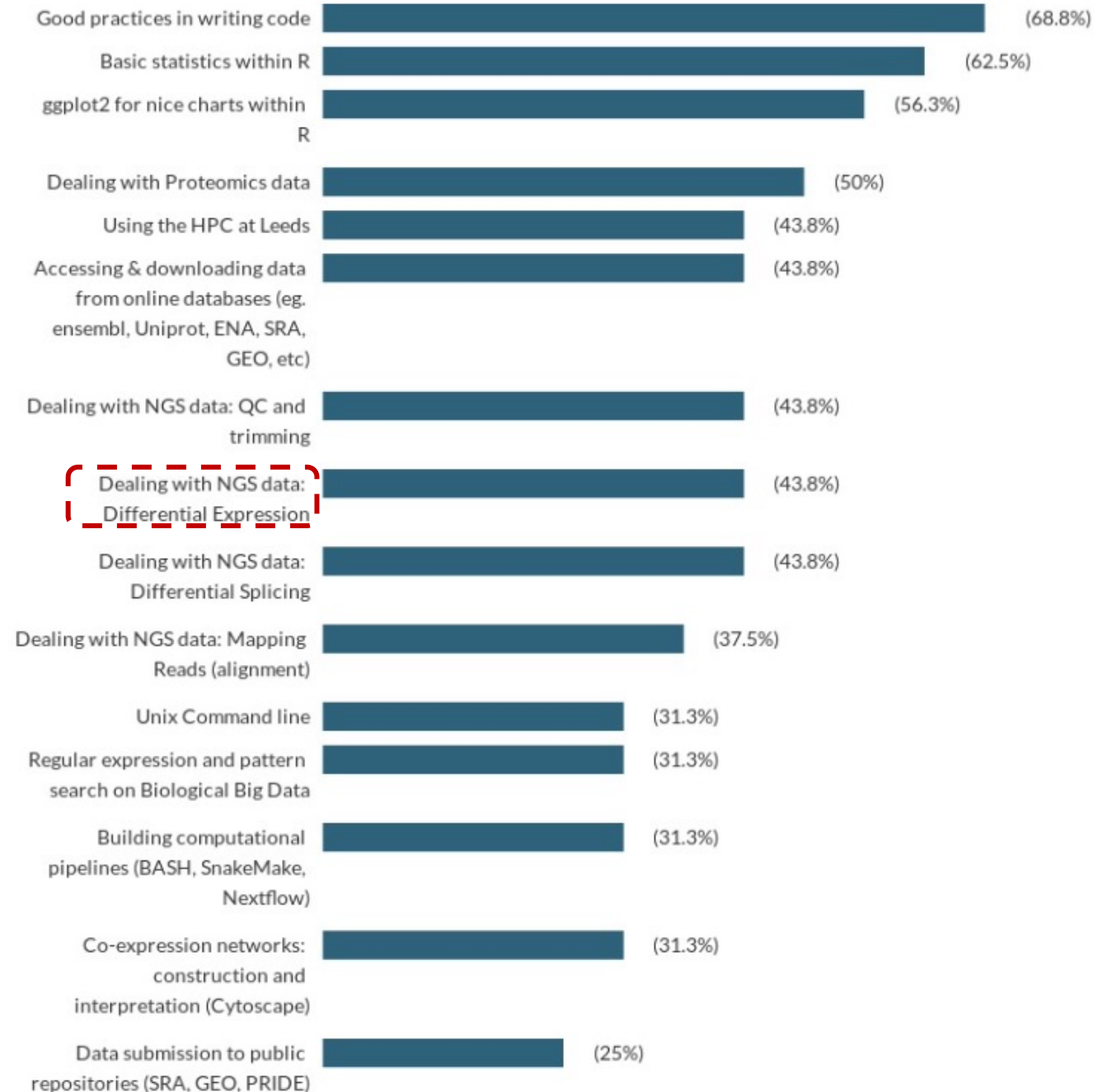


[www.leedsomics.org](http://www.leedsomics.org)  
@leedsomics  
[omics@leeds.ac.uk](mailto:omics@leeds.ac.uk)

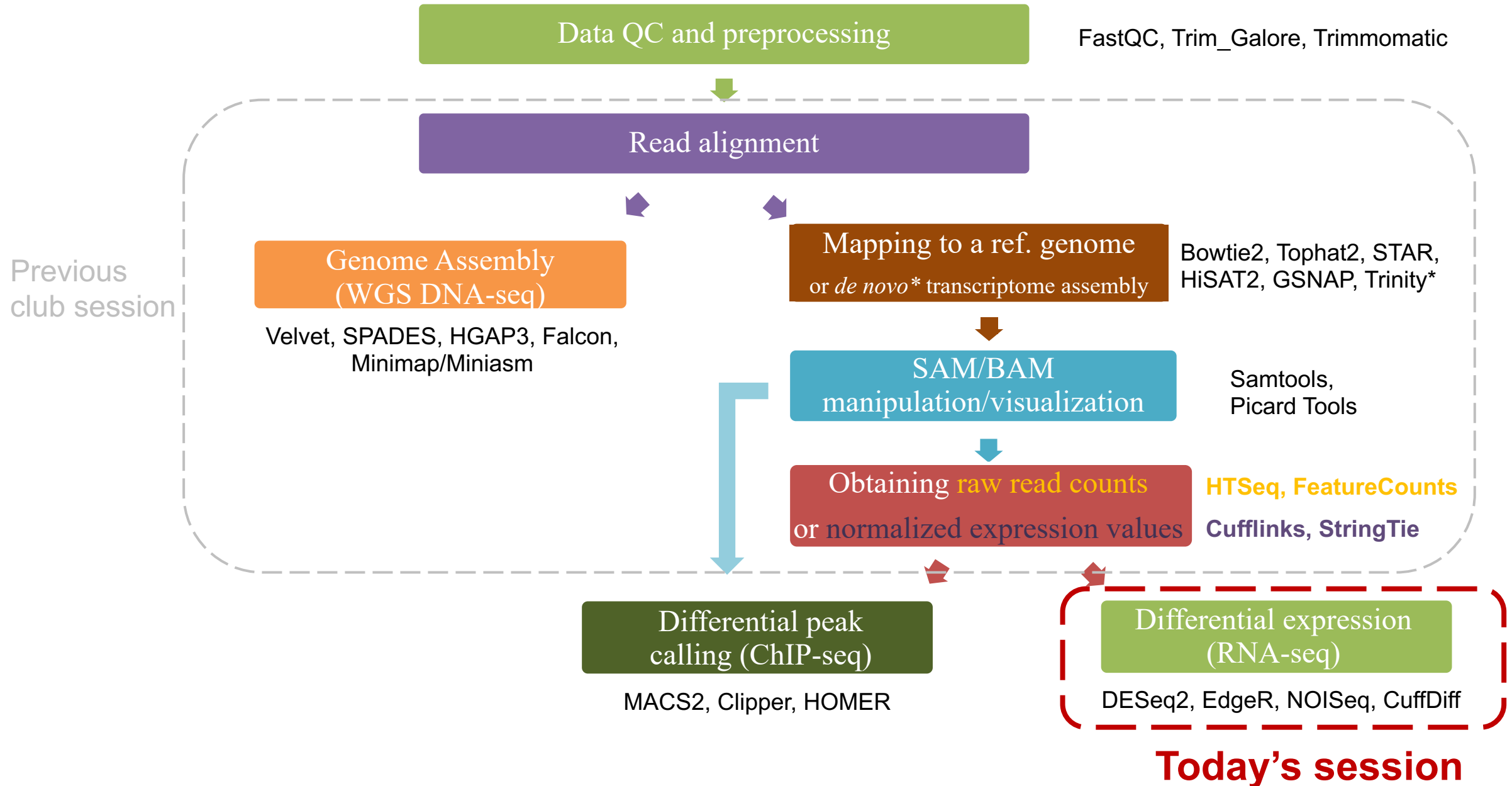
# Dealing with NGS data: Differential Expression

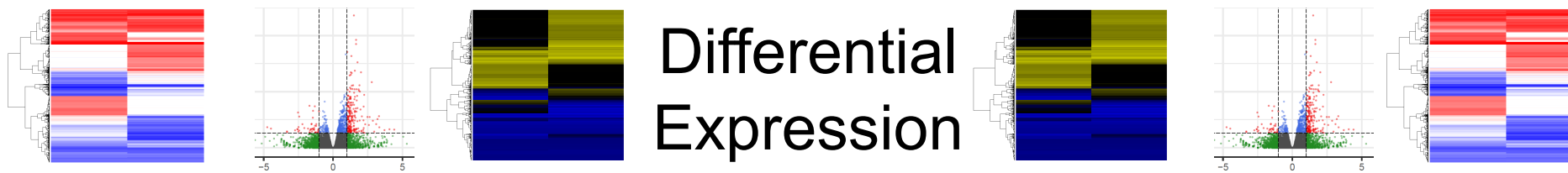
**Club Moderators:** Elton Vasconcelos and Euan McDonell

# Topics to be addressed - Survey Result (2021-22)



# Important steps on NGS data analysis workflow





## Software packages for DE analysis

Method	Version	Reference	Normalization <sup>a</sup>	Read count distribution assumption	Differential expression test
edgeR	3.0.8	[ 4 ]	<u>TMM</u> /Upper quartile/RLE (DESeq-like)/None (all scaling factors are set to be one)	Negative binomial distribution	Exact test
DESeq	1.10.1	[ 5 ]	DESeq sizeFactors	Negative binomial distribution	Exact test
baySeq	1.12.0	[ 6 ]	Scaling factors ( <u>quantile</u> /TMM/total)	Negative binomial distribution	Assesses the posterior probabilities of models for differentially and non-differentially expressed genes via empirical Bayesian methods and then compares these posterior likelihoods
NOIseq	1.1.4	[ 7 ]	<u>RPKM</u> /TMM/Upper quartile	Nonparametric method	Contrasts fold changes and absolute differences within a condition to determine the null distribution and then compares the observed differences to this null
SAMseq (samr)	2.0	[ 8 ]	SAMseq specialized method based on the mean read count over the null features of the data set	Nonparametric method	Wilcoxon rank statistic and a resampling strategy
Limma	3.14.4	[ 9 ]	TMM	voom transformation of counts	Empirical Bayes method
Cuffdiff2 (Cufflinks)	2.0.2-beta	[ 10 ]	<u>Geometric</u> (DESeq-like)/quartile/classic-fpkm	Beta negative binomial distribution	<i>t</i> -test
EBSeq	1.1.7	[ 11 ]	DESeq median normalization	Negative binomial distribution	Evaluates the posterior probability of differentially and non-differentially expressed entities (genes or isoforms) via empirical Bayesian methods

<sup>a</sup> In case of availability of several normalization methods, the default one is underlined.

→ **Important Output Metrics:**  $\log_2(\text{FC})$ , p-value and FDR provided in most output files

# The DESeq2 model

- Perform a “*median of ratios*” normalization to correct for library size and RNA composition bias (counts divided by sample-specific size factors determined by median ratio of gene counts relative to geometric mean per gene);
- Use shrinkage estimation for dispersions and fold changes because small numbers of replicates make it impossible to estimate within-group variance reliably;
- Fit negative binomial generalized linear models for each gene and uses the Wald test for significance testing.

# Prepare the data for DESeq2 analysis

countData: a matrix of non-negative integers

	normal.rep1	normal.rep2	normal.rep3	tumor.rep1	tumor.rep2	tumor.rep3
ENSG00000283047	0	0	0	1	1	0
ENSG00000283023	1	1	1	0	0	3
ENSG00000280341	0	0	1	0	1	1
ENSG00000279442	0	2	0	0	0	0
ENSG00000237299	0	0	0	3	0	3
ENSG00000233408	0	0	0	0	0	1
ENSG00000215268	1	0	1	0	0	0
ENSG00000230471	0	0	0	0	0	1
ENSG00000231565	0	0	0	2	1	2

colData: a DataFrame with at least a single column. Rows of colData correspond to columns of countData.

	condition
normal.rep1	normal
normal.rep2	normal
normal.rep3	normal
tumor.rep1	tumor
tumor.rep2	tumor
tumor.rep3	tumor

design: a formula expressing the variables which will be used in modelling.

# The main three steps of running DESeq2

1. Create a DESeqDataSet object from input. Please note that the colnames of countData must be identical to the rownames of colData.

```
dds <- DESeqDataSetFromMatrix(countData = count.data.keep,  
colData = coldata, design = ~ condition)
```

2. Perform the differential expression analysis.

```
dds <- DESeq(dds, fitType = "local")
```

3. Extract a results table.

```
res <- results(dds)
```

Bring your issues on!