



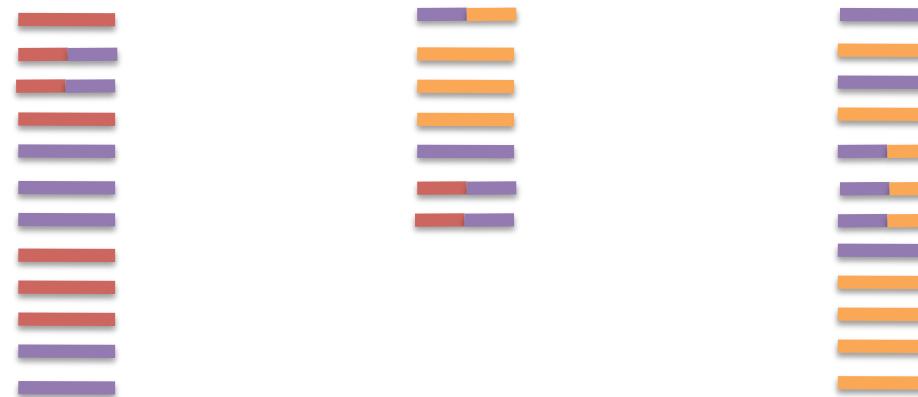
Ballgown

flexible RNA-seq differential expression analysis

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Johns Hopkins Biostatistics
@acfrazee

RNA-seq data

Reads
(50-100
bases)



Transcripts
(RNA)

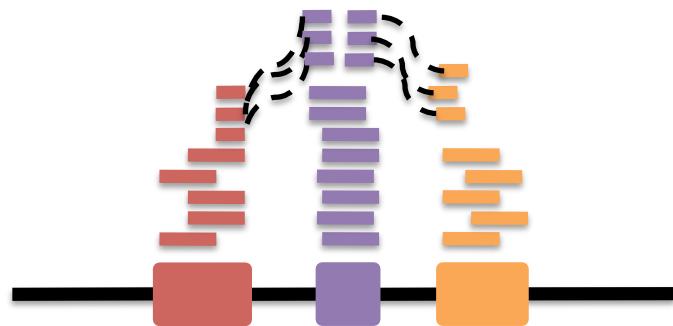


Genome
(DNA)



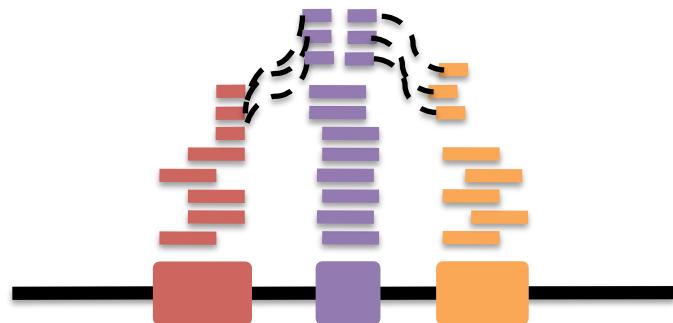
RNA-seq data analysis

align



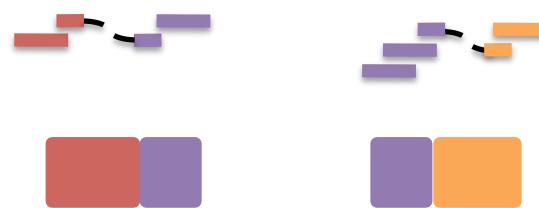
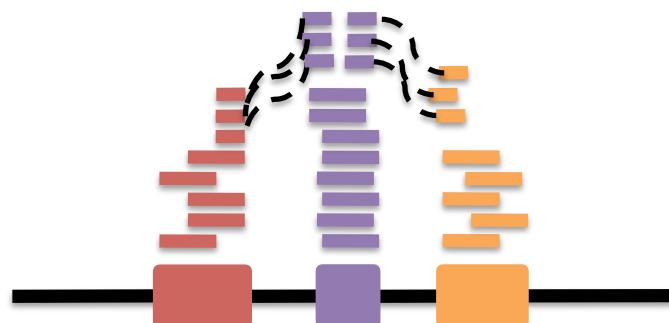
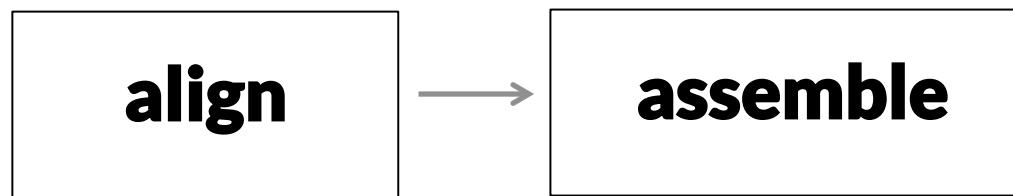
RNA-seq data analysis

align



(or not: *de novo* assembly)

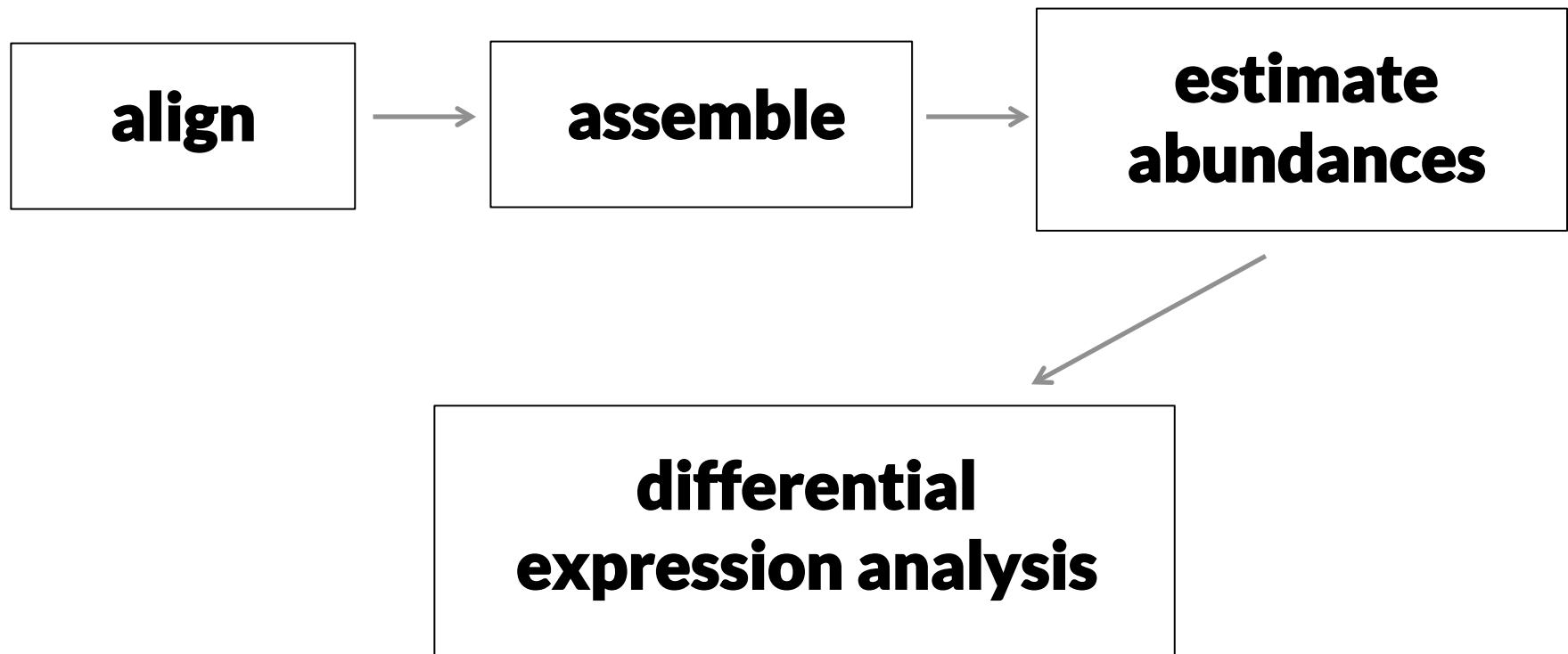
RNA-seq data analysis



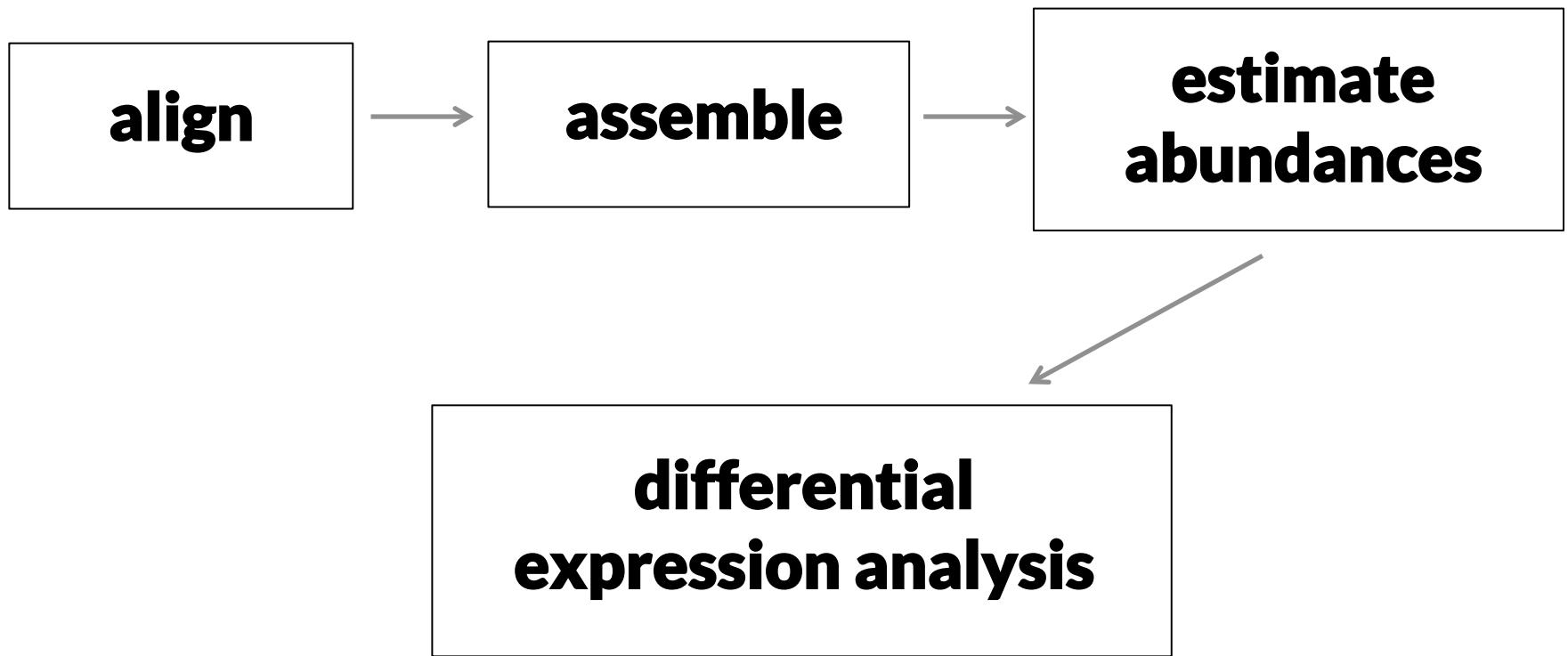
RNA-seq data analysis



RNA-seq data analysis

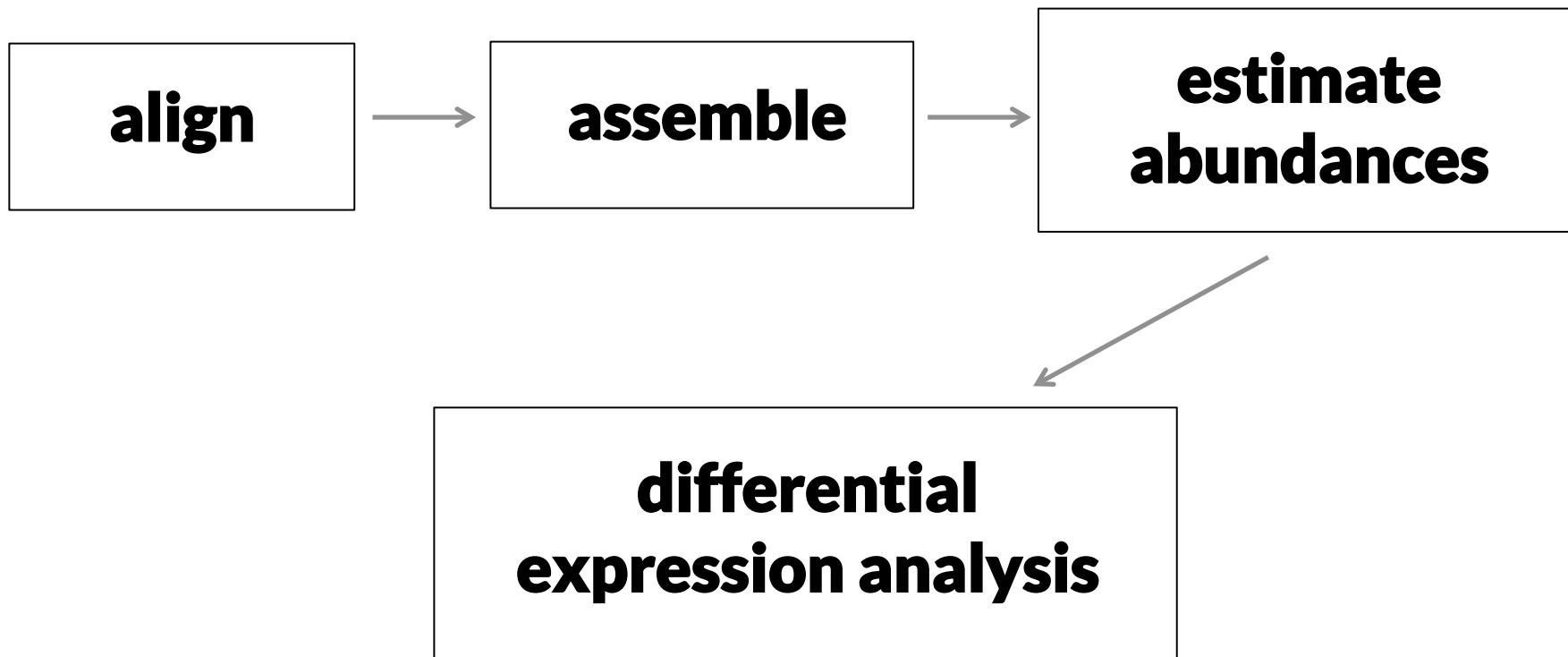


RNA-seq data analysis



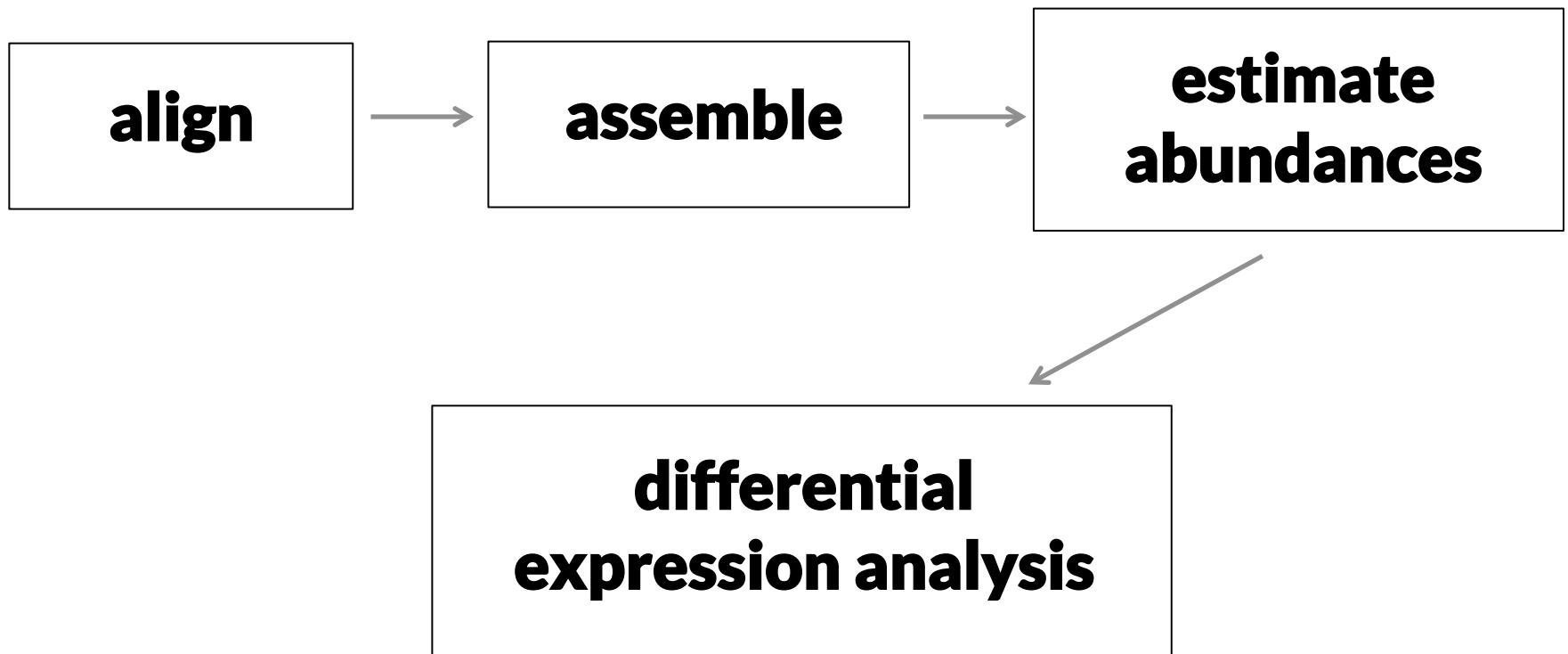
**Is transcript X expressed differently in population A
vs. population B?**

RNA-seq data analysis



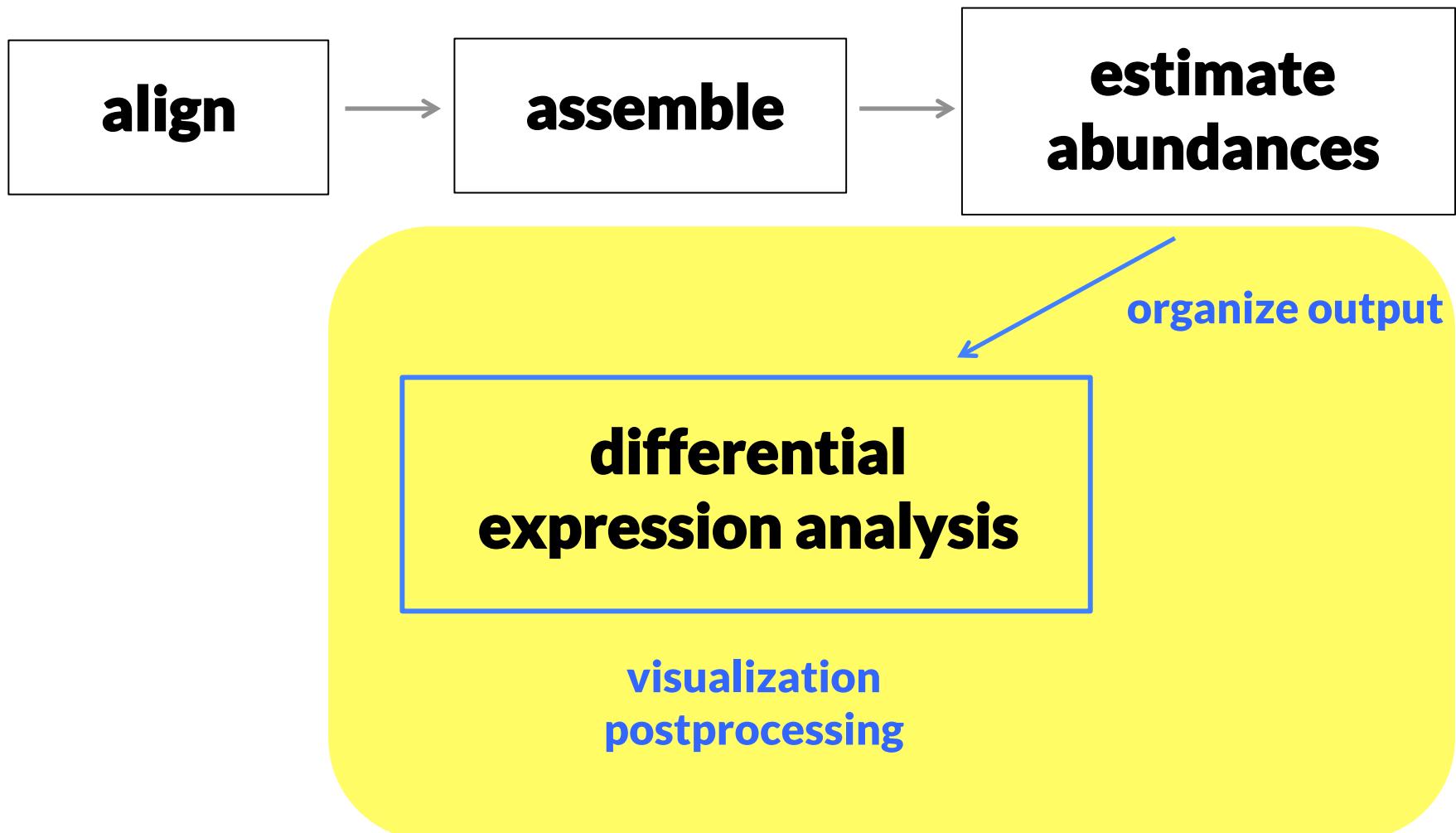
**Is transcript X expressed differently in population A
vs. population B vs. population C?**

RNA-seq data analysis



Is transcript X expressed constantly over the course of time in the study?

Ballgown



organize output: Tablemaker

```
top_dir/
    sample01/
        e2t.ctab
        e_data.ctab
        i2t.ctab
        i_data.ctab
        t_data.ctab
    sample02/
        e2t.ctab
        e_data.ctab
        i2t.ctab
        i_data.ctab
        t_data.ctab
    sample03/
        e2t.ctab
        e_data.ctab
        i2t.ctab
        i_data.ctab
        t_data.ctab
```

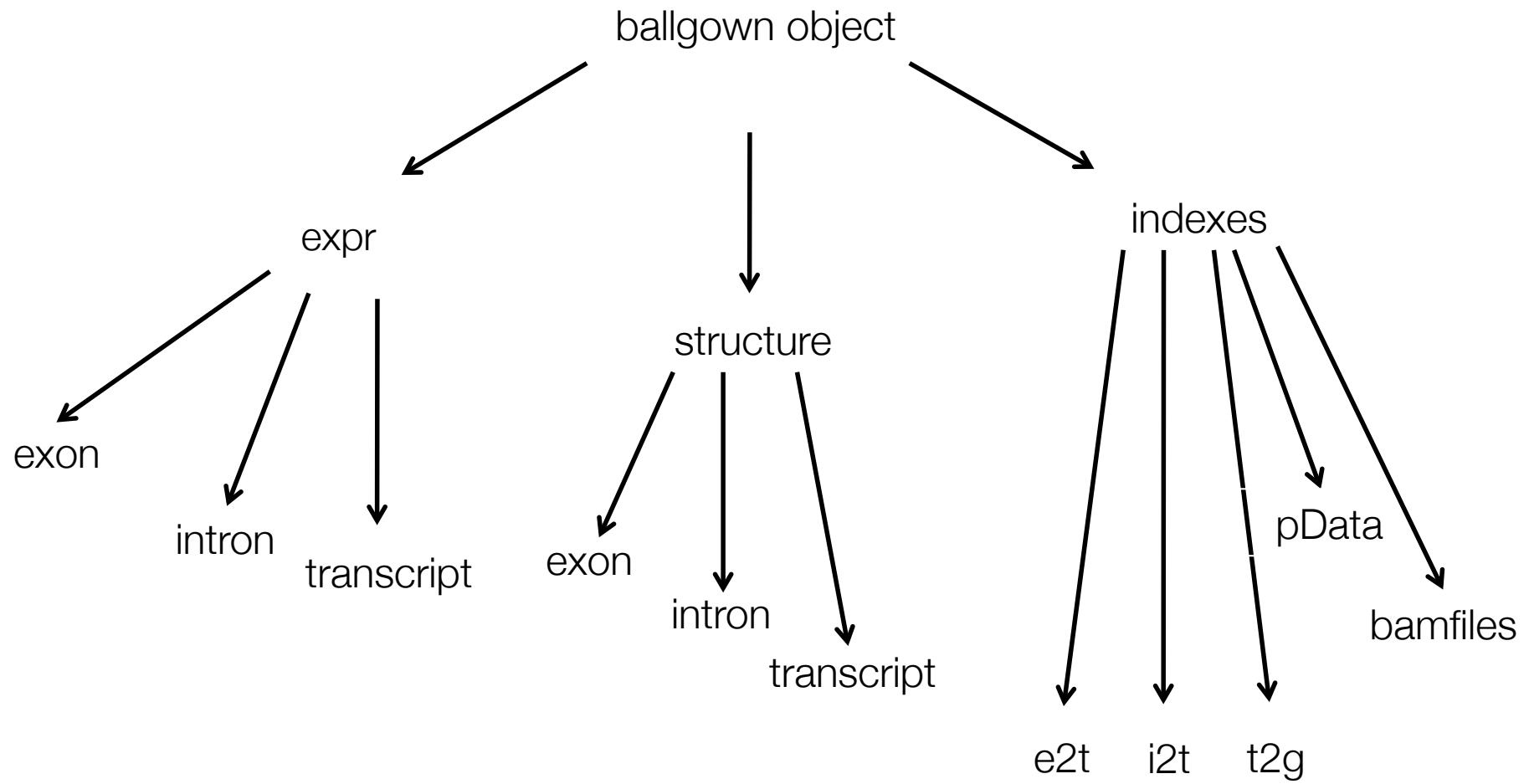
S4 class for transcript assemblies

```
library(ballgown)

my_assembly = ballgown(dataDir='top_dir', samplePattern=
  'sample')
my_assembly
## ballgown instance with 124892 transcripts and 3 samples

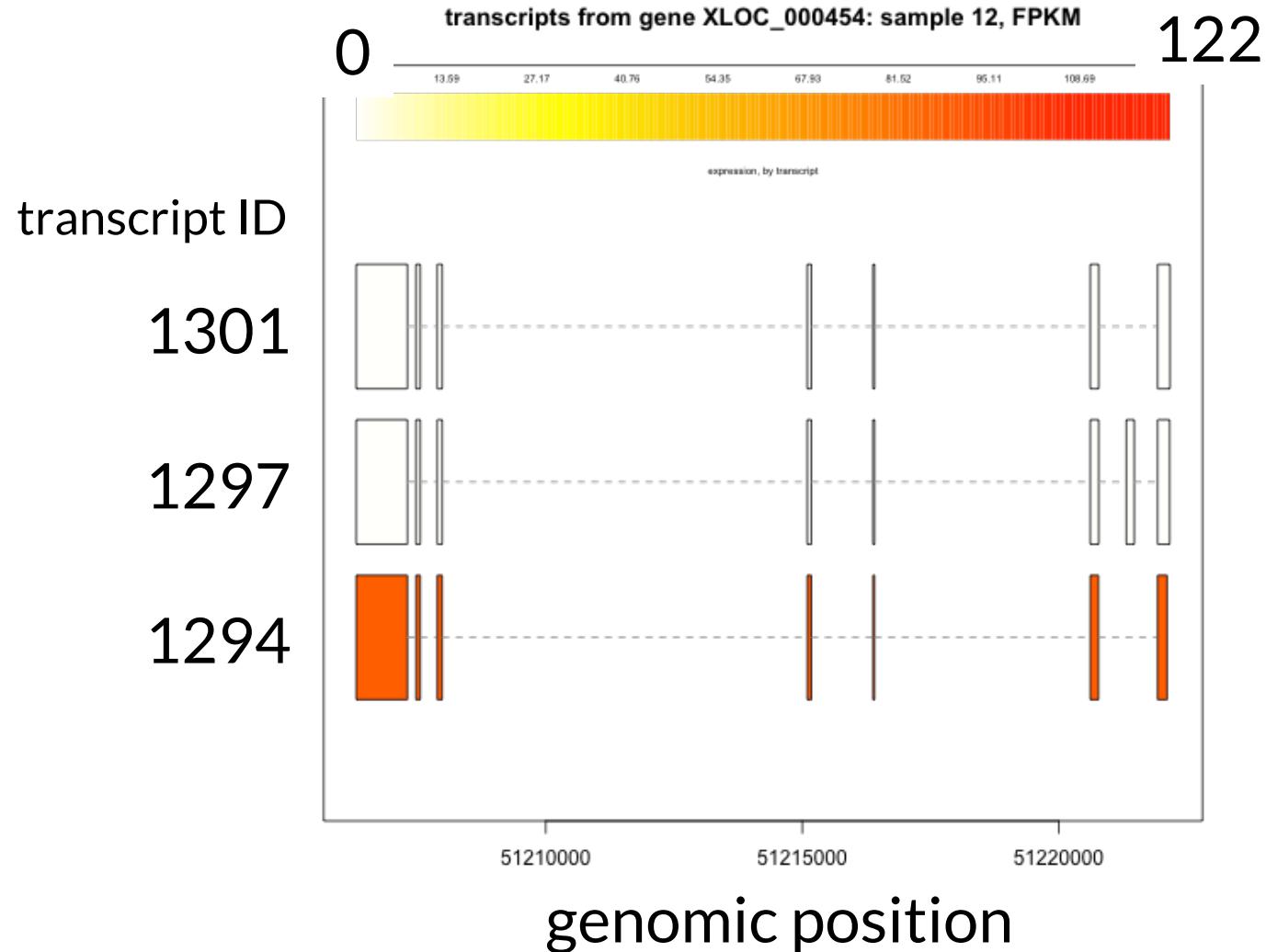
my_rsem_assembly = ballgownrsem(dir='top_dir', samples=
  c('sample01', 'sample02', 'sample03'),
  gtf='hg19_genes.gtf')
my_rsem_assembly
## ballgown instance with 45914 transcripts and 3 samples
```

S4 class for transcript assemblies



convenient visualization

```
plotTranscripts(gene='XLOC_000454', gown=my_assembly,  
samples='sample12', meas='FPKM', colorby='transcript',  
main='transcripts from gene XLOC_000454: sample 12, FPKM')
```



fast, flexible statistical analysis

```
stat_results = stattest(my_assembly, feature='transcript',
meas='FPKM', covariate='group')

head(stat_results)
## #> #> feature id pval qval
## #> transcript 10 0.01381576 0.105212332
## #> transcript 25 0.26773622 0.791149753
## #> transcript 35 0.01085070 0.089518254
## #> transcript 41 0.47108019 0.902537475
## #> transcript 45 0.08402948 0.489348136
## #> transcript 67 0.27317385 0.79114975
```

drop-in replacement for Cuffdiff

fast, flexible statistical analysis

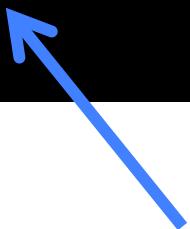
```
stat_results = stattest(my_assembly, feature='transcript',
meas='FPKM', covariate='group')

head(stat_results)
## #> #> feature id pval qval
## #> transcript 10 0.01381576 0.105212332
## #> transcript 25 0.26773622 0.791149753
## #> transcript 35 0.01085070 0.089518254
## #> transcript 41 0.47108019 0.902537475
## #> transcript 45 0.08402948 0.489348136
## #> transcript 67 0.27317385 0.79114975
```

drop-in replacement for Cuffdiff
bonus: handles more experimental designs!

timecourse

```
stat_results = stattest(my_assembly, feature='transcript',  
                      meas='FPKM', covariate='group')  
  
timecourse_results = stattest(my_assembly,  
                             feature='transcript', meas='FPKM', covariate='time',  
                             timecourse=TRUE)
```



models expression over time as smooth curve;
compares to model where expression is assumed constant over time

custom models

```
stat_results = stattest(my_assembly, feature='transcript',
    meas='FPKM', covariate='group')

timecourse_results = stattest(my_assembly,
    feature='transcript', meas='FPKM', covariate='time',
    timecourse=TRUE)

mod = model.matrix(~ time + library_size)
mod0 = model.matrix(~ library_size)
my_timecourse_results = stattest(my_assembly,
    feature='transcript', meas='FPKM', mod=mod, mod0=mod0)
```

easy integration with other packages

```
stat_results = stattest(my_assembly, feature='transcript',
meas='FPKM', covariate='group')

timecourse_results = stattest(my_assembly,
feature='transcript', meas='FPKM', covariate='time',
timecourse=TRUE)

mod = model.matrix(~ time + library_size)
mod0 = model.matrix(~ library_size)
my_timecourse_results = stattest(my_assembly,
feature='transcript', meas='FPKM', mod=mod, mod0=mod0)

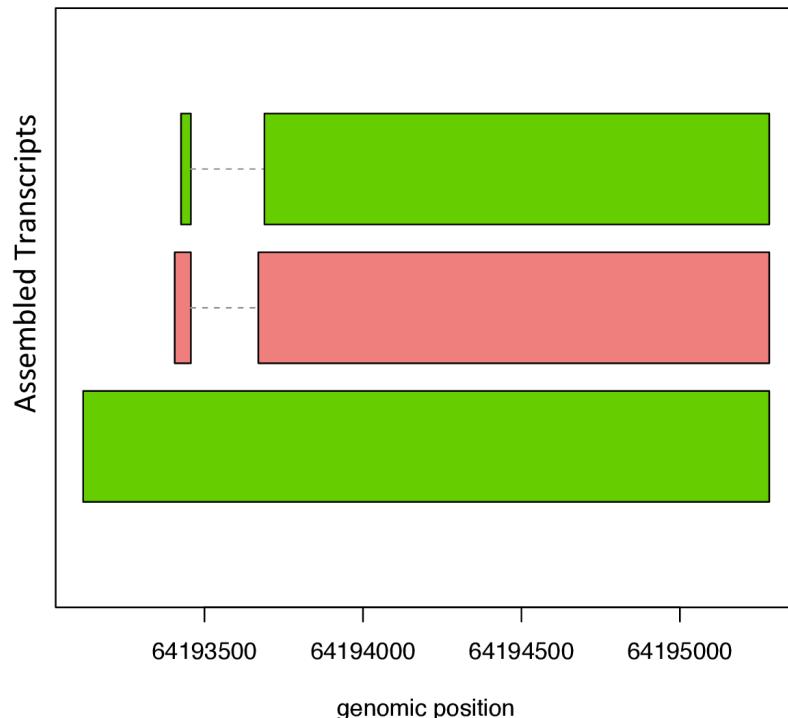
library(limma)
expression_mat = log2(exprs(my_assembly, 'FPKM') + 1)
fit = lmFit(y, mod)
fit = eBayes(fit, trend=TRUE)
```

wrangling large datasets

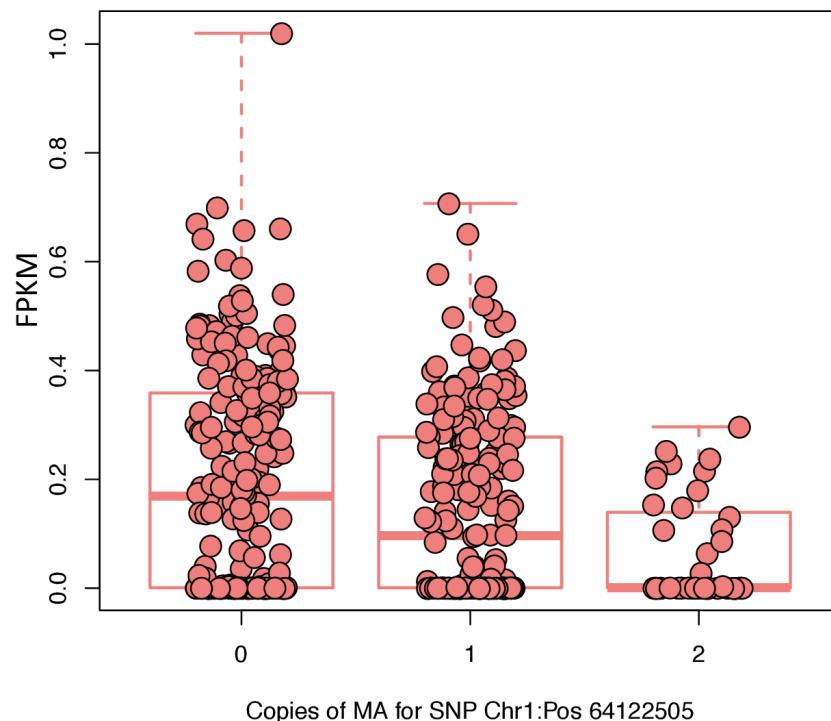
reanalysis of GEUVADIS data: eQTL

a

Chr1:64193406–64195282



b



wrangling large datasets

reanalysis / processing of GEUVADIS data

Ballgown objects: figshare

TopHat read alignments: ArrayExpress (E-GUV-6)

analysis code: GitHub,
https://github.com/alyssafrazee/ballgown_code

thanks!

Collaborators: Jeff Leek (advisor), Geo Pertea, Andrew Jaffe, Ben Langmead, Steven Salzberg

References:

[manuscript](http://biorxiv.org/content/early/2014/03/30/003665): <http://biorxiv.org/content/early/2014/03/30/003665>

[limma](#): “Linear models for Microarray Data” by Gordon K Smyth, in Bioinformatics and Computational Biology Solutions using R and Bioconductor, Springer 2005

[Cufflinks](#): PMID 20436464 (Trapnell et al 2010)

[RSEM](#): PMID 21816040 (Li & Dewey 2011)

Software: Ballgown is under Bioconductor review; currently available and fully documented at <https://github.com/alyssafrazee/ballgown>

differential expression model

for each transcript, compare the fits of the following models using an F-test. Null hypothesis is that the fits of model (a) and model (b) are equally good; alternative is that (a) fits better.

$$(a) \text{ expression}_i = \alpha + \beta_0 \text{group}_i + \sum_{p=1}^P \gamma_p \text{confounder}_{ip} + \text{noise}_{ip}$$

$$(b) \text{ expression}_i = \alpha^* + \sum_{p=1}^P \gamma_p^* \text{confounder}_{ip} + \text{noise}_{ip}^*$$