

#### Hidden layers of complexity How small RNA distribution and sample handling affect sequencing results

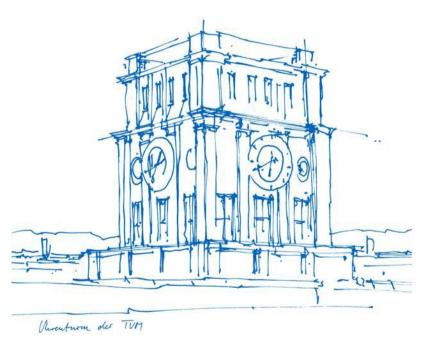
Dr. Benedikt Kirchner

Technische Universität München

School of Life Sciences

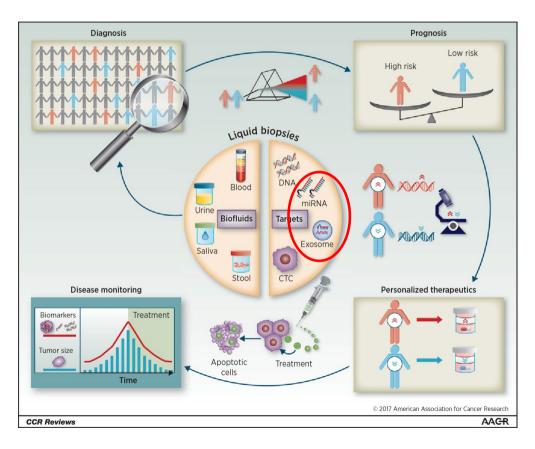
Division of Animal Physiology and Immunology

June 30<sup>th</sup>, 2023



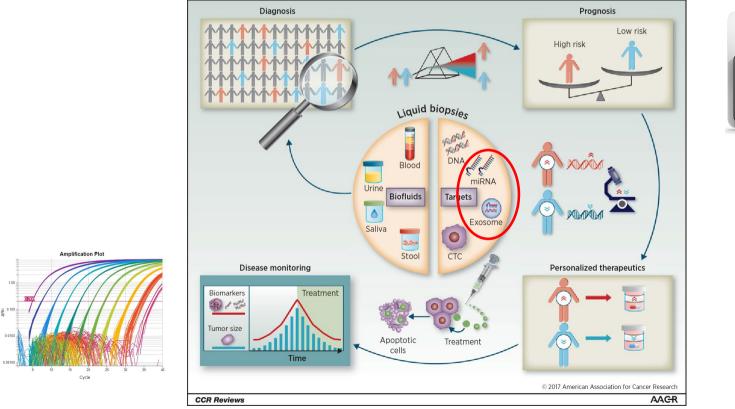


# Biomarker development in clinical settings



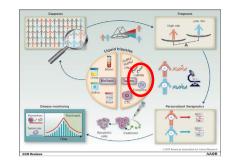


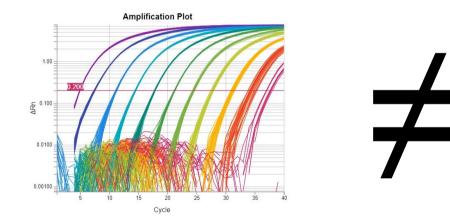
# Biomarker development in clinical settings



Norther (50)

### Disagreement in methods

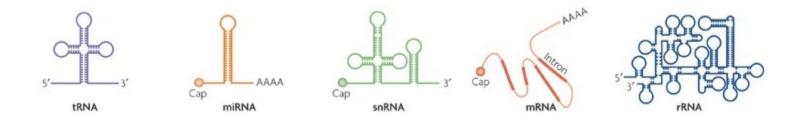






# Size selection bias in small RNA NGS



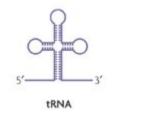


#### Enrichment of RNAs smaller than ~50 nt

Köhler et al, Nature Reviews Molecular Cell Biology 2007

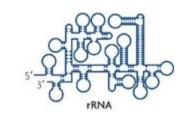
# Size selection bias in small RNA NGS

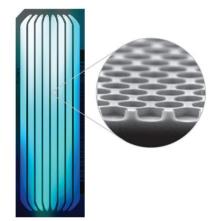










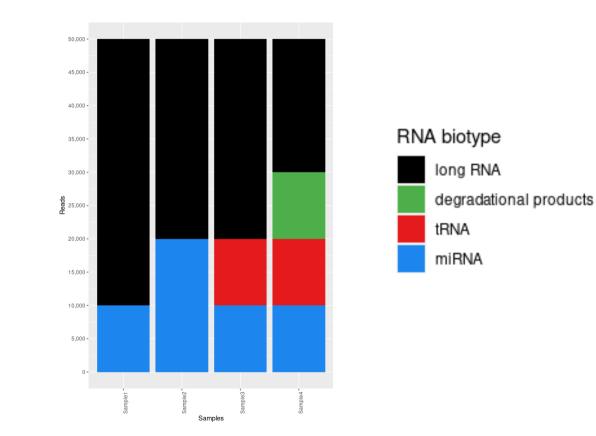


- Finite number of reads per flowcell
- Quantification always in relation to other small RNA transcripts
- Spike-in controls still rarely used

Köhler et al, Nature Reviews Molecular Cell Biology 2007

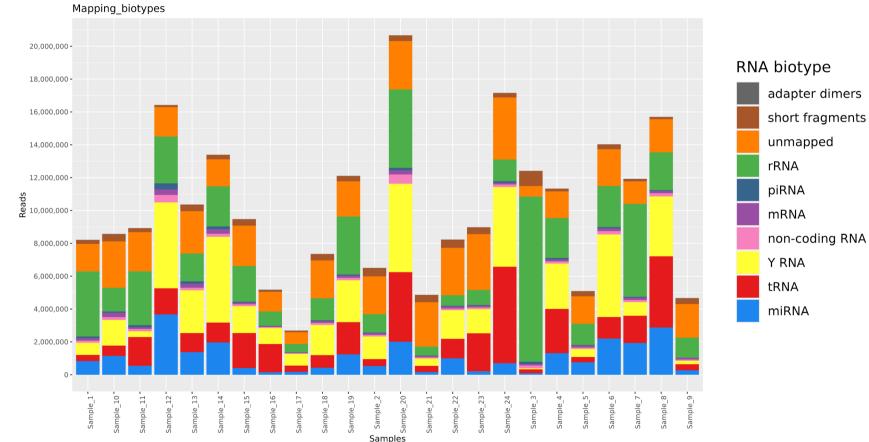
# Importance of normalization strategies

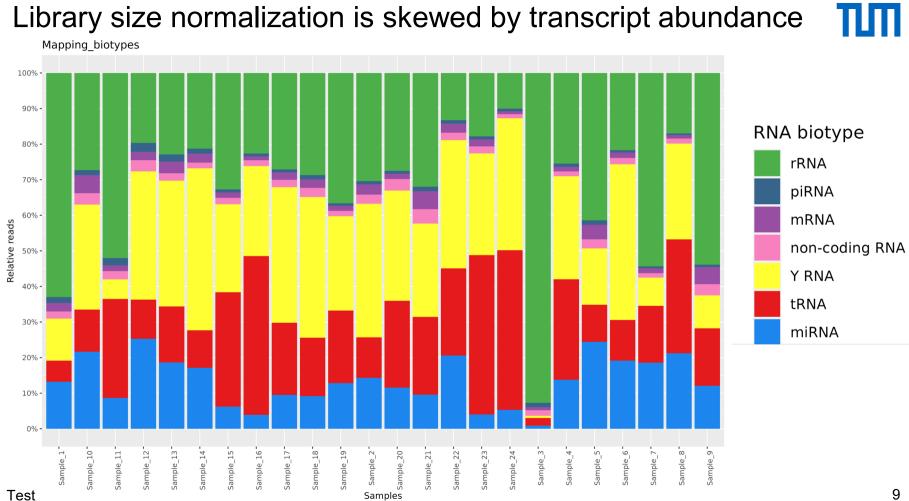


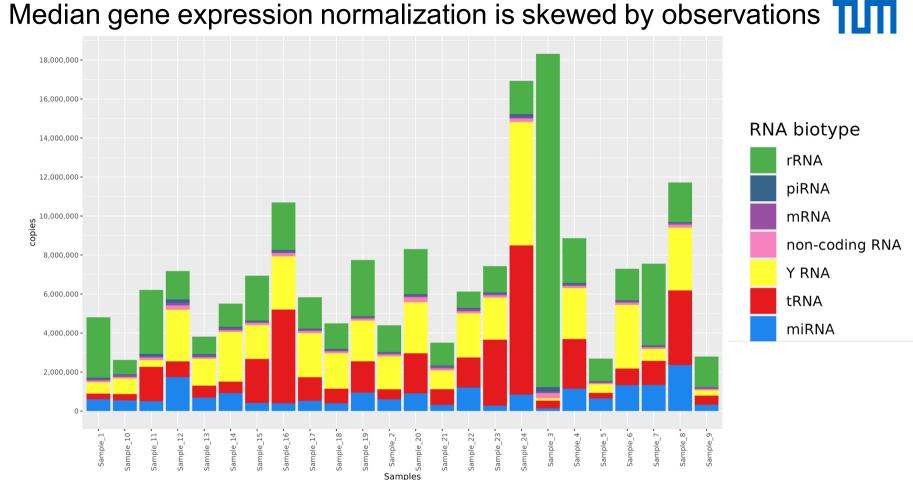


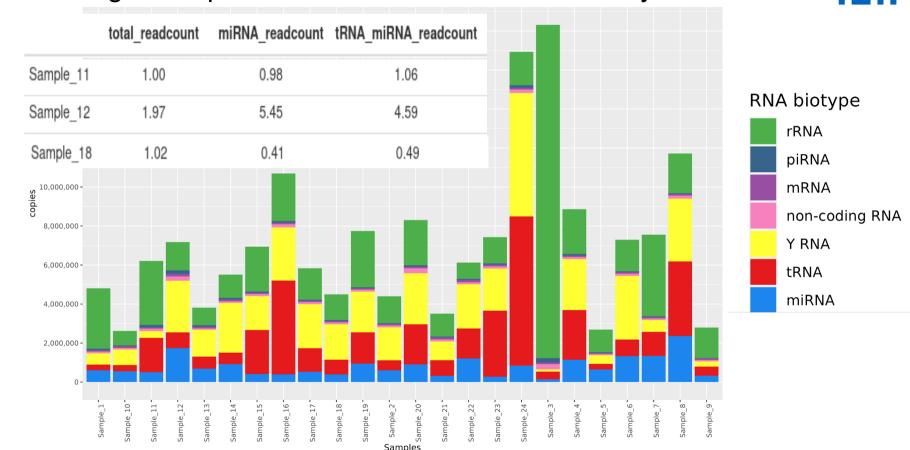
# Heterogenous biotype distribution







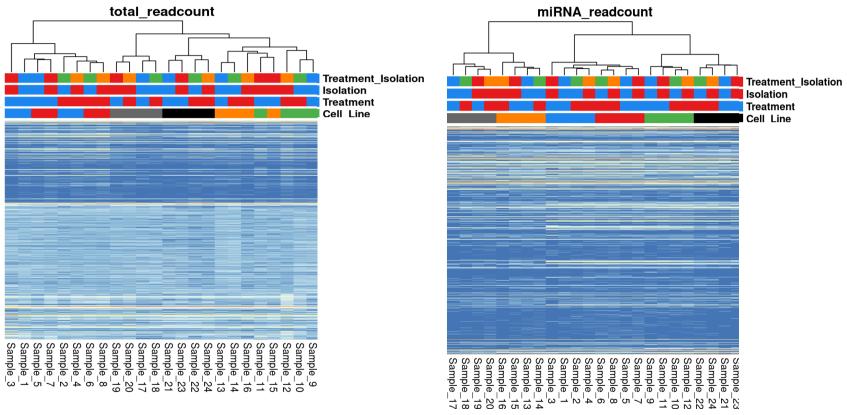




### Median gene expression normalization is skewed by observations

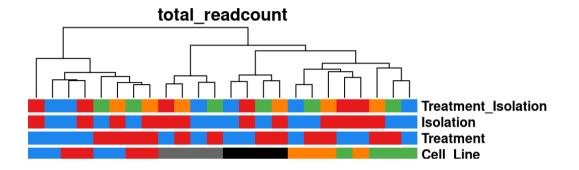
# Normalization can be a major source of bias





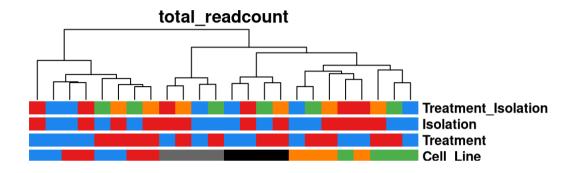
# Normalization can be a major source of bias

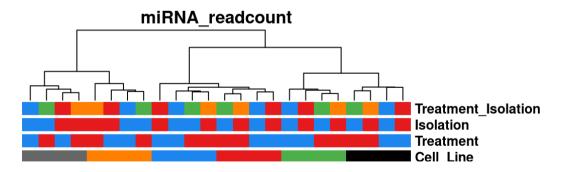




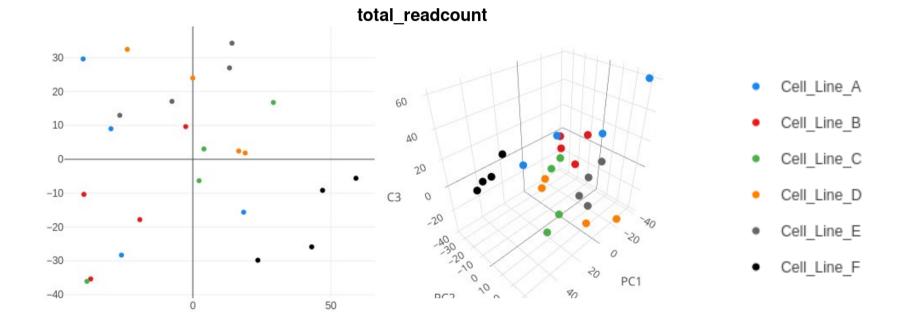
# Normalization can be a major source of bias







# Correct normalization enables batch effect detection



ПΠ

75 -70

5

PC1

0

5

10

# 16

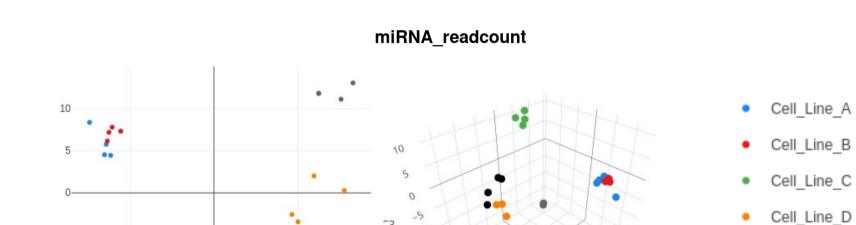
Cell Line E

Cell Line F

.

.

ΠП



5

10

-15

10

PC2

5

0

5

23

# Correct normalization enables batch effect detection

-5

-10

-15

-10

٠

•

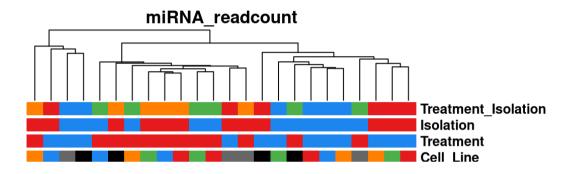
0

••

10

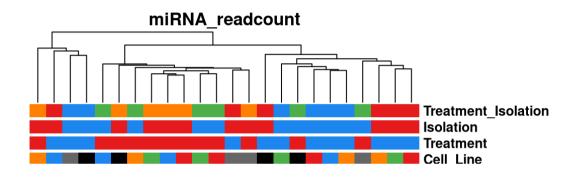
# Exploit small RNA NGS beyond miRNAs

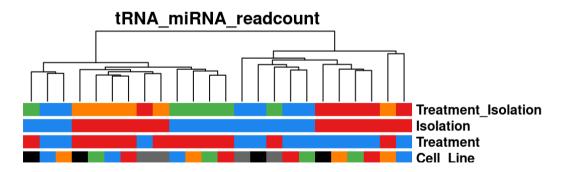




# Improvement of normalization in small RNA NGS

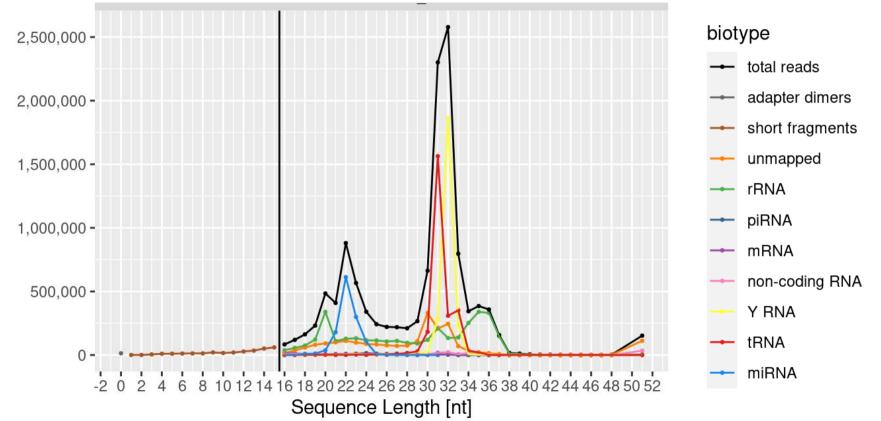






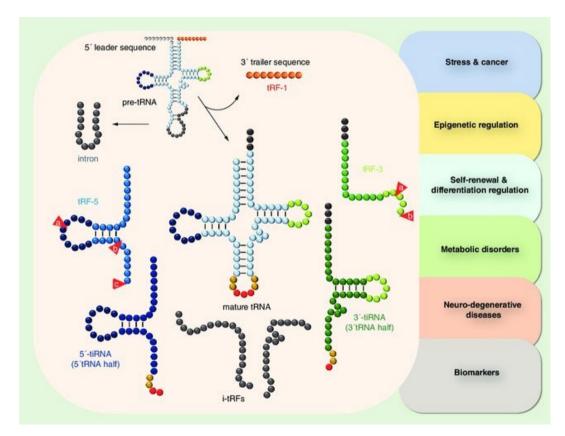
# Degradation vs Specificity in small RNAs





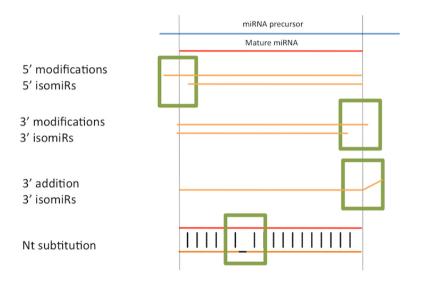
# Hidden complexity in small RNA NGS - tRFs

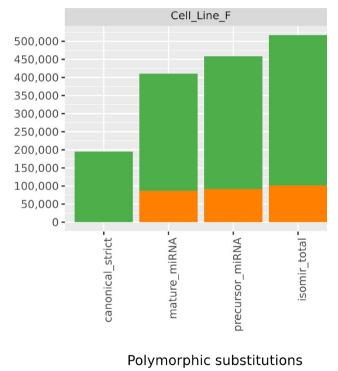




# Hidden complexity in small RNA NGS - isomiRs







0

# Hidden complexity in small RNA NGS - isomiRs



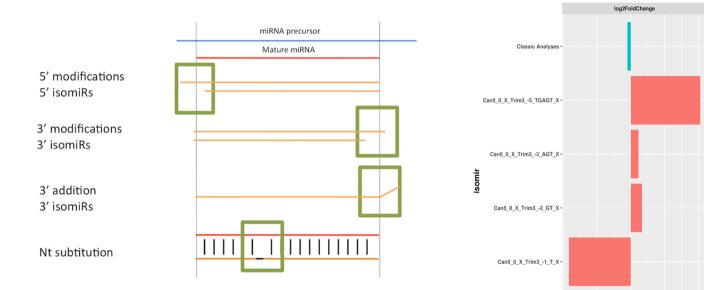
RP10M

adjusted p-value <= 0.05 > 0.05

20000

30000

10000



Isomir vs Classic Analyses hsa-miR-181a-5p

Can5\_0\_X\_Can3\_0\_X\_X -

-2.5

-5.0

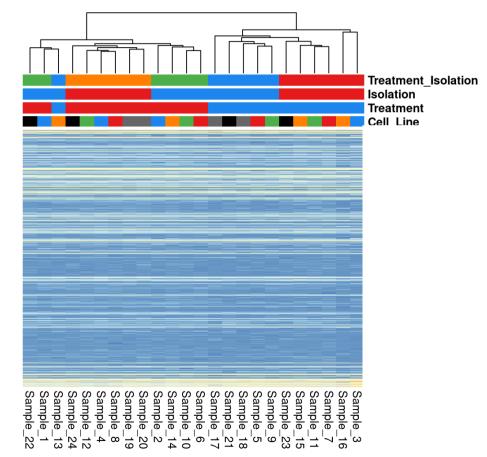
0.0

2.5

5.0

log2 Fold Change

Comprehensive analysis of small RNA transcriptome increases efficiency of biomarker detection



tRFs + isomiRs



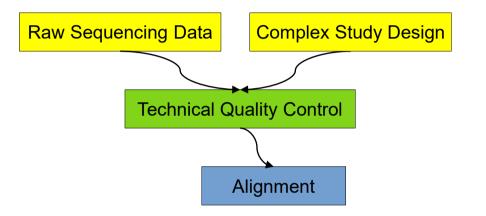
## Conclusions

- Importance of spike-ins in small RNA NGS
- Comprehensive characterization of full transcriptome necessary for correct normalization
  and batch effect detection
- Detection of functional fragments and isoforms increases specificity in classification and biomarker profiles

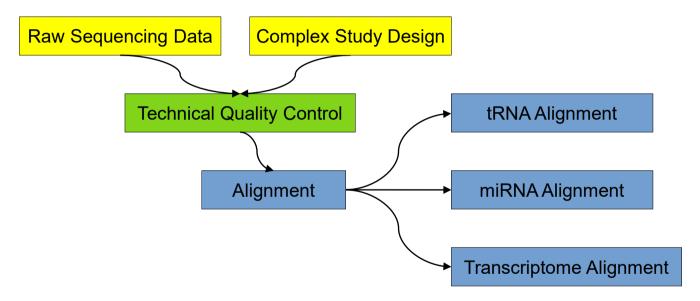


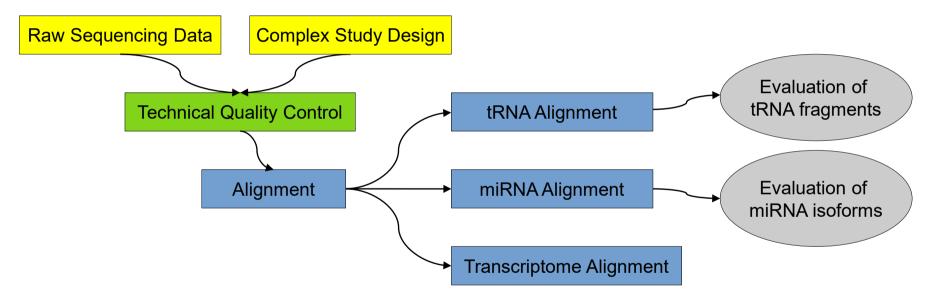
• Detection of stable reference transcripts in small RNA NGS for biomarker validation



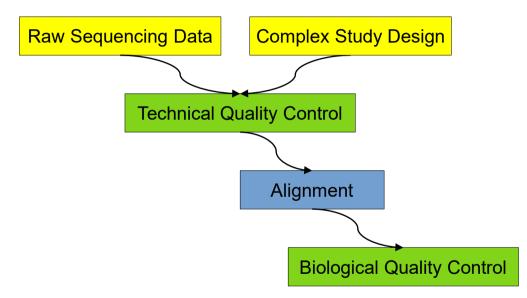




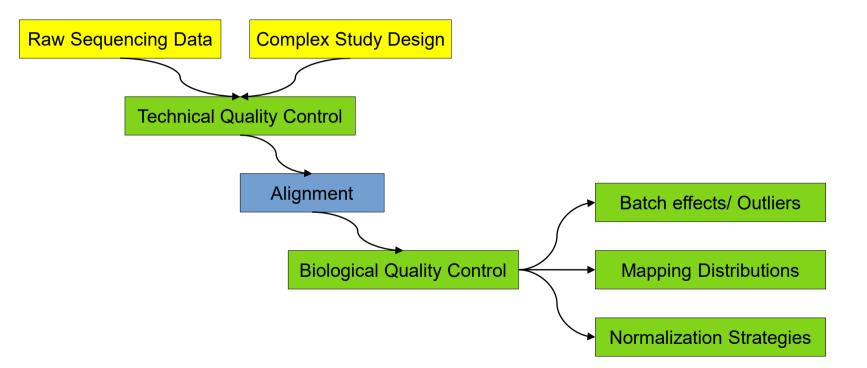




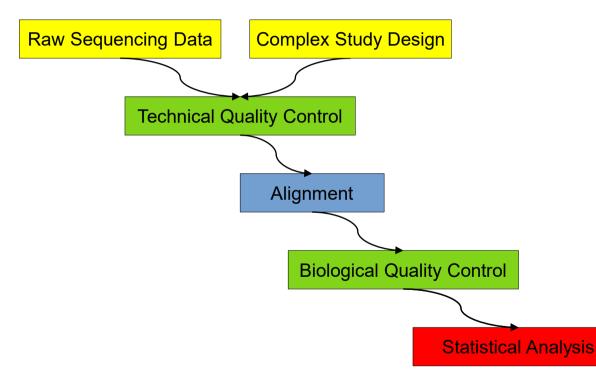




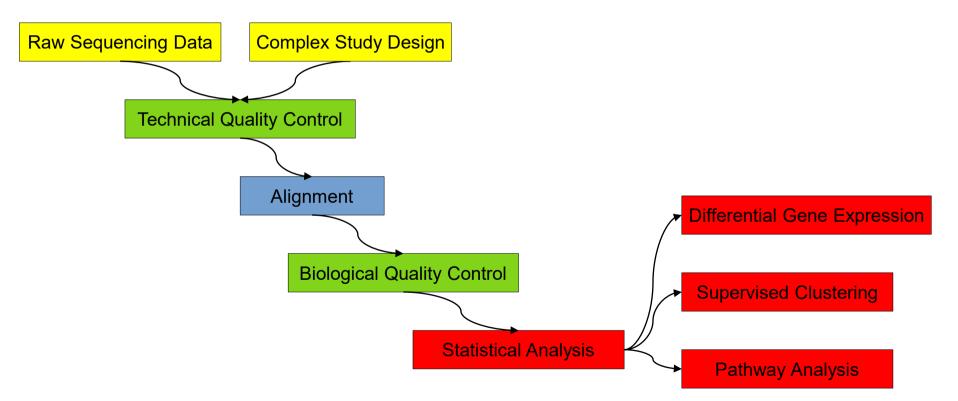












#### Output

#### **Quality Control**

- Detection of degradational status
- Detection of sequencing errors
- Detection of batch effects
- Detection of outliers
- Relative distribution of all RNA species
- Length distribution of alignments

#### Pathway and gene list analysis

- Identification of predicted and experimentally validated targets of mature miRNAs
- Overrepresentation analysis of significantly regulated transcripts
  - o Gene Ontology
  - KEGG
  - o Reactome
  - o WikiPathways

#### Differential gene expression

- Normalization according to specified RNA species
- Statistical evaluation of gene expression changes
- Pairwise comparisons of all specified experimental groups
- Evaluation of stable reference transcripts for qPCR validation

#### microRNA and isomiR analysis

- Integrative differential transcript analysis between predominant isomiRs and parent miRNAs
- Analysis of miRNA clusters
- Detection of miRNA localization motifs
- Evaluation of miRNA stability by isomiR modifications

#### Supervised clustering

- Detection of optimal error rates
- Sparse projection on latent squares (sPLS)
- Classification based on biomarker profiles



## Acknowledgements

- Division of Animal Physiology and Immunology, TUM
  - Prof. Michael Pfaffl
- Research Group Big Data in Biomedicine, TUM
  - Johannes Kersting
- Institute of Human Genetics, LMU
  - Marlene Reithmair
  - Martina Schuster





