

ANR

Monopoly ANR project :

Integrated gene network analyses between mono- and poly-ovulating species



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INRAE

GenROC team



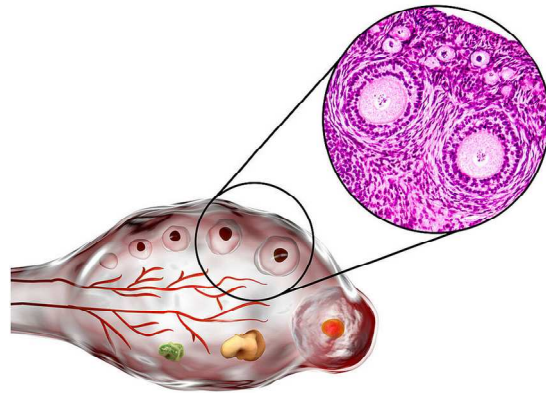
GenPhySE
Génétique Physiologie et Systèmes d'Élevage



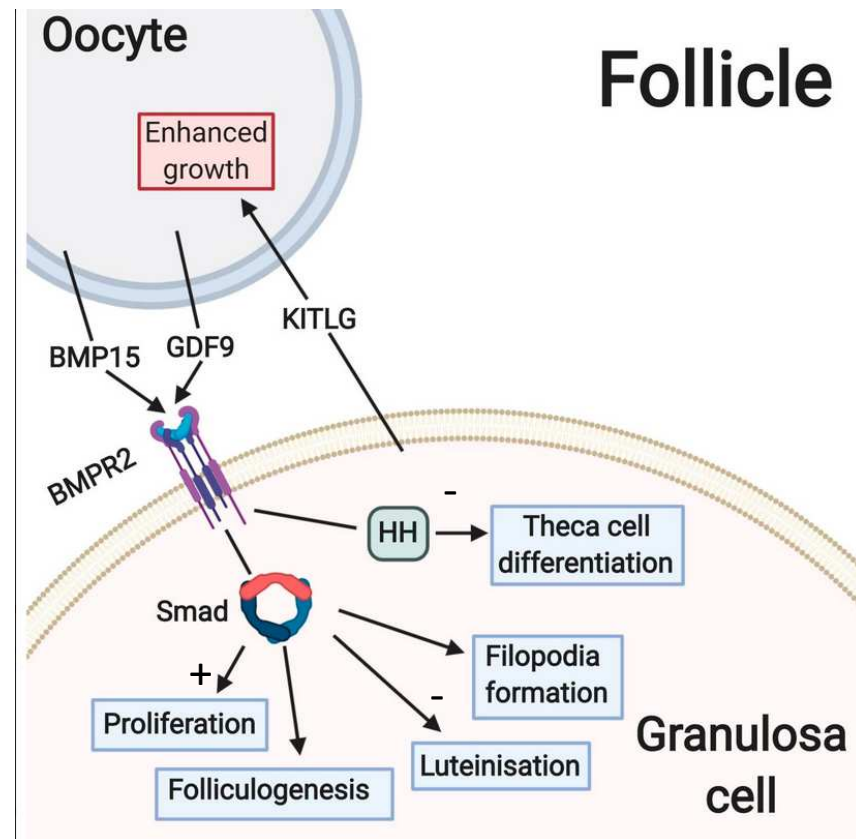
> Context

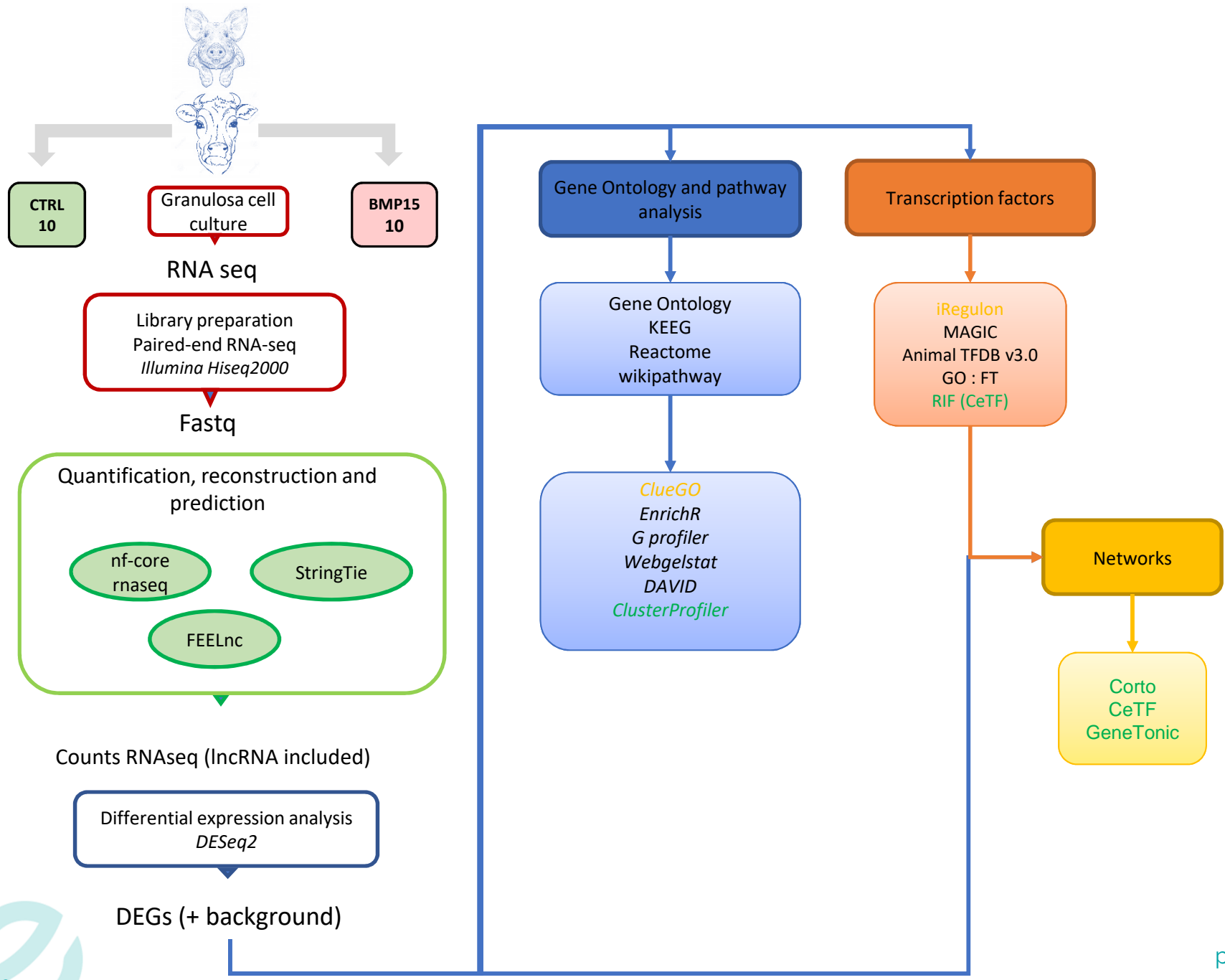
Folliculogenesis is important for the development and maintenance of fertility

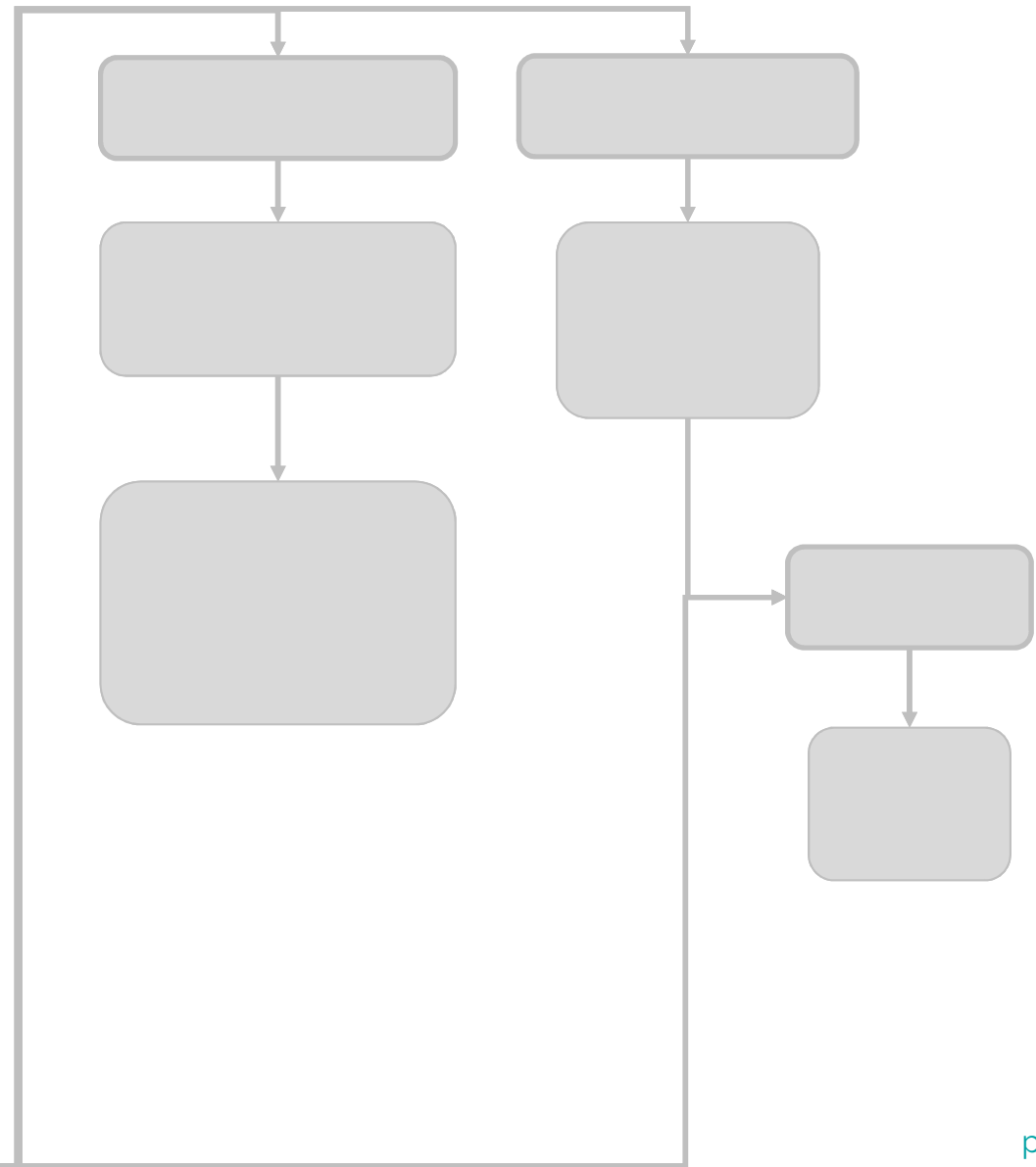
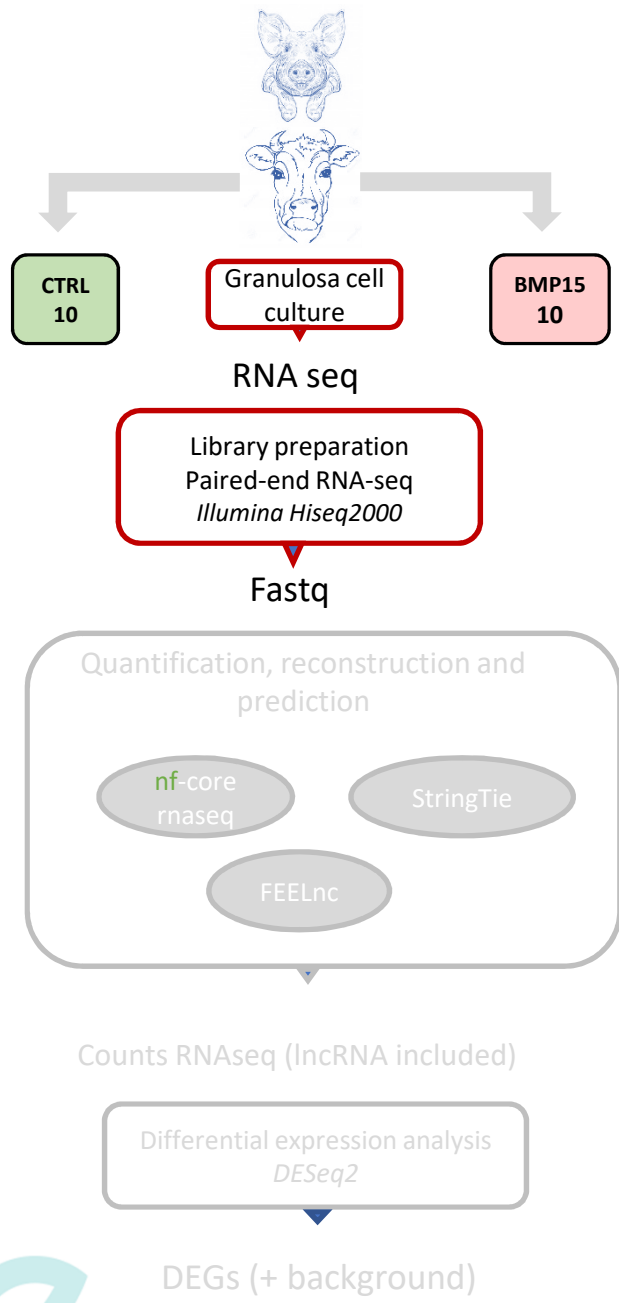
Ovarian microcosmos.



- BMP15 protein
- Secreted ligand of the TGF- β superfamily
- Involved in folliculogenesis
- Contributed to paracrine dialog

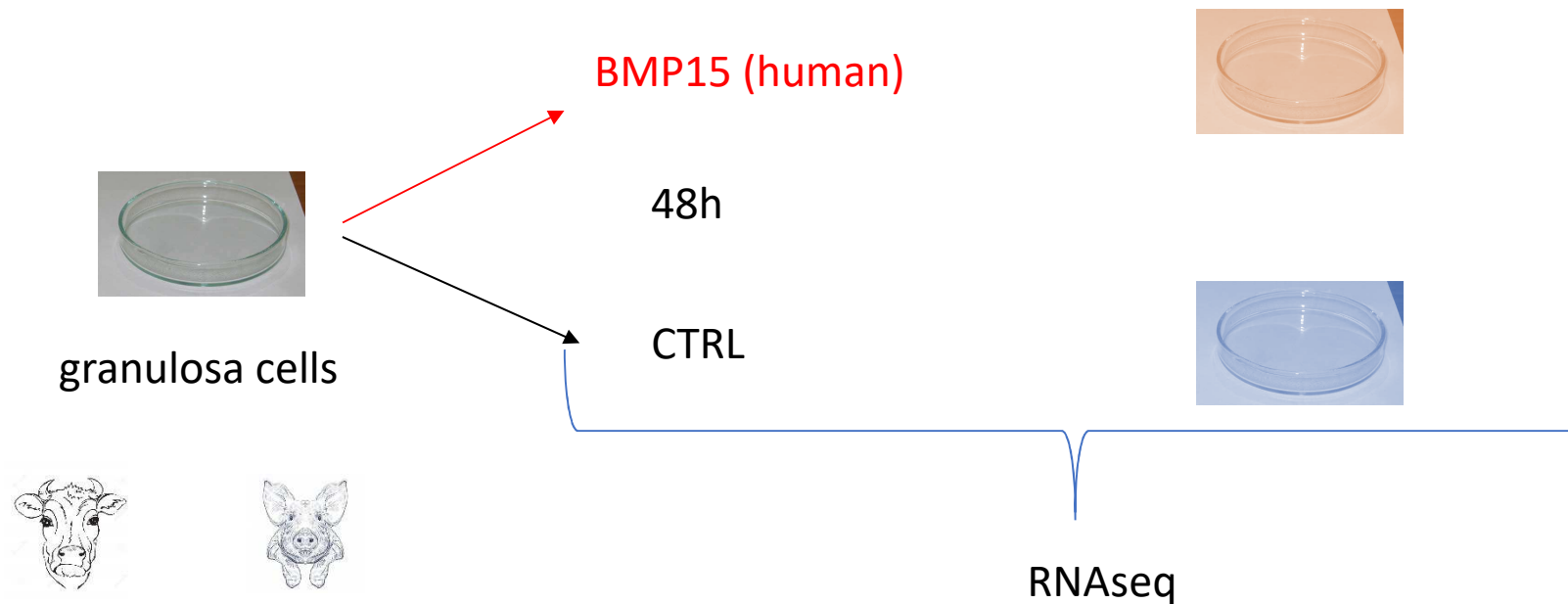






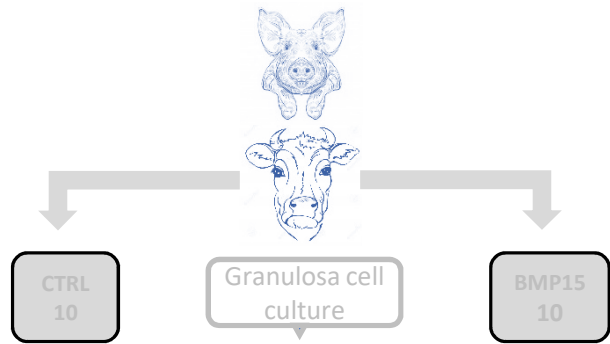
➤ Monopoly ANR project (2010 S. Fabre)

Decipher BMP15 response in granulosa cells of cow and sow (mono vs poly-ovulating species)



20 samples by species (10 CTRL vs 10 BMP15)

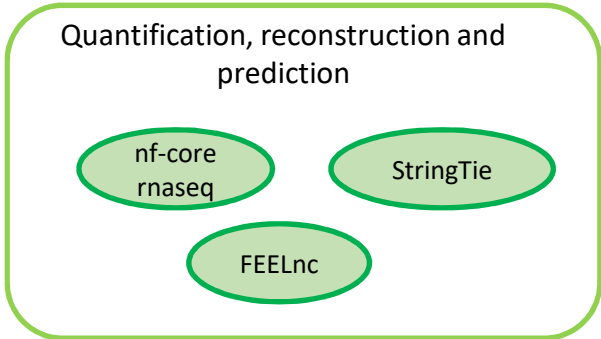
40 sequencing lanes ($0,94 < \text{Pearson Correlation} < 0,98$)



RNA seq

Library preparation
Paired-end RNA-seq
Illumina HiSeq2000

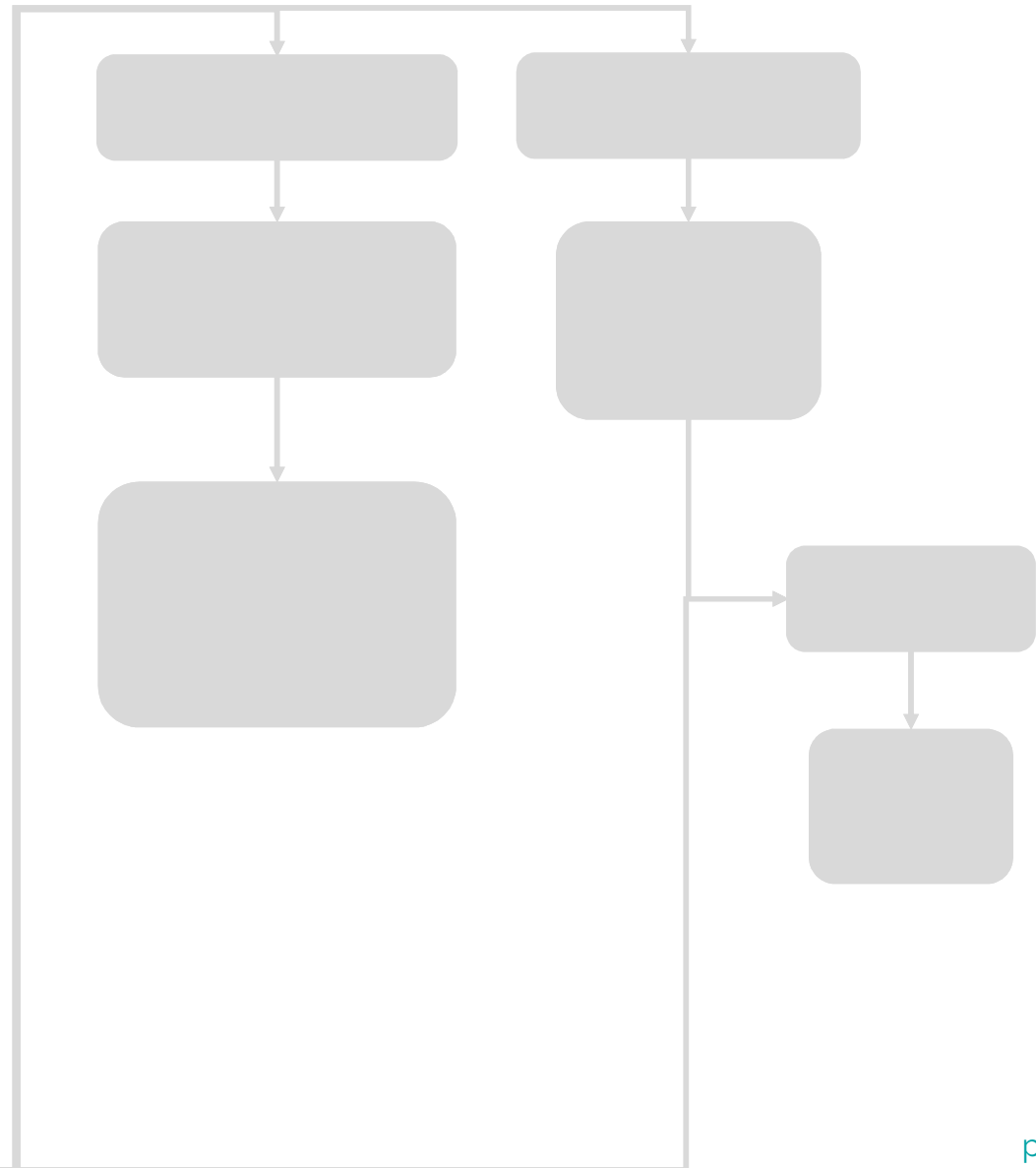
Fastq



Counts RNAseq (lncRNA included)

Differential expression analysis
DESeq2

DEGs (+ background)



nf-core

A community effort to collect a curated set of analysis pipelines built using Nextflow.

[VIEW PIPELINES](#)



For facilities

Highly optimised pipelines with excellent reporting. Validated releases ensure reproducibility.



For users

Portable, documented and easy to use workflows. Pipelines that you can trust.



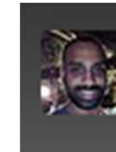
For developers

Companion templates and tools help to validate your code and simplify common tasks.

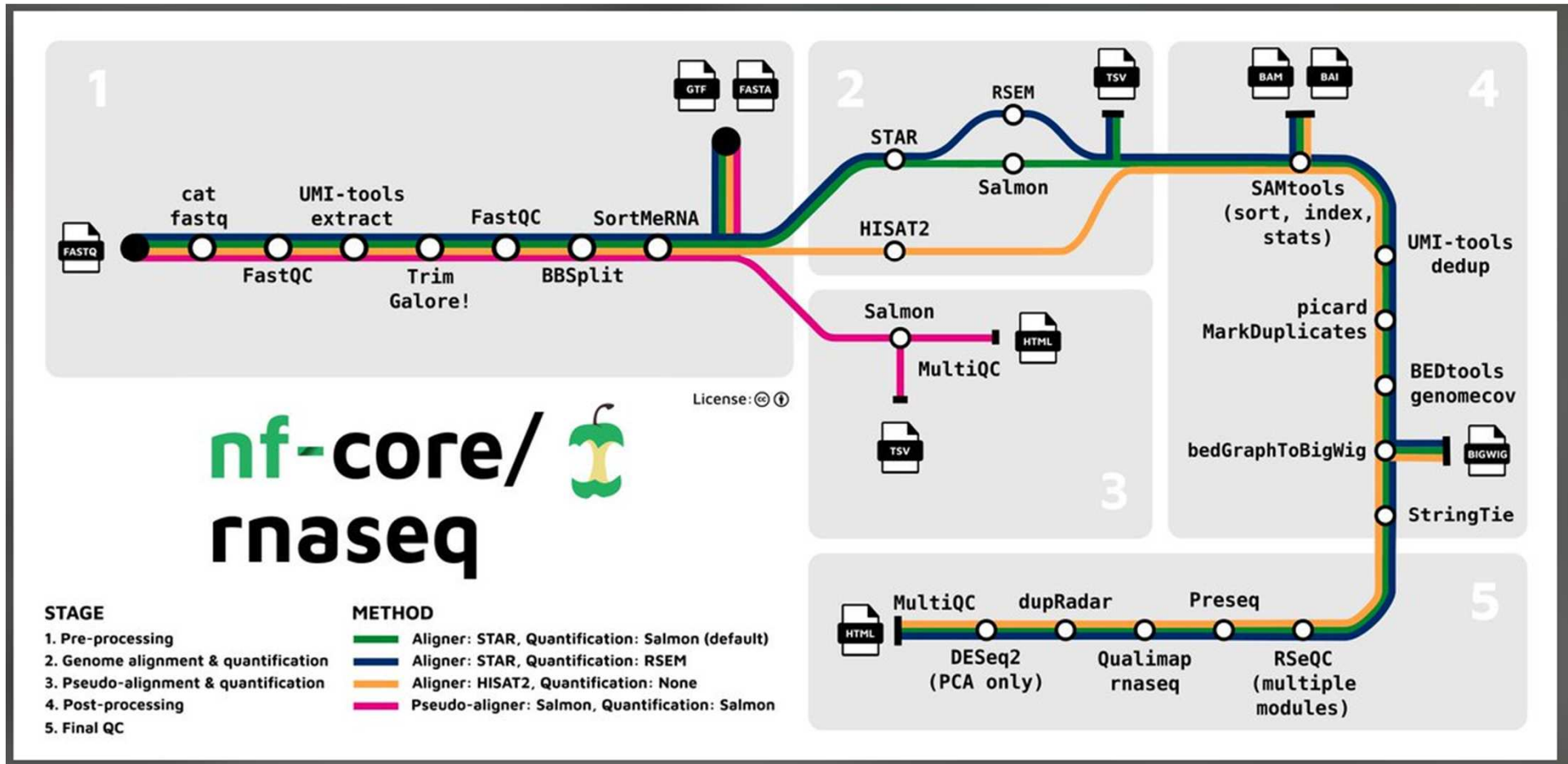


nf-core is published in Nature Biotechnology!

[Nat Biotechnol 38, 276–278 \(2020\).](#) 



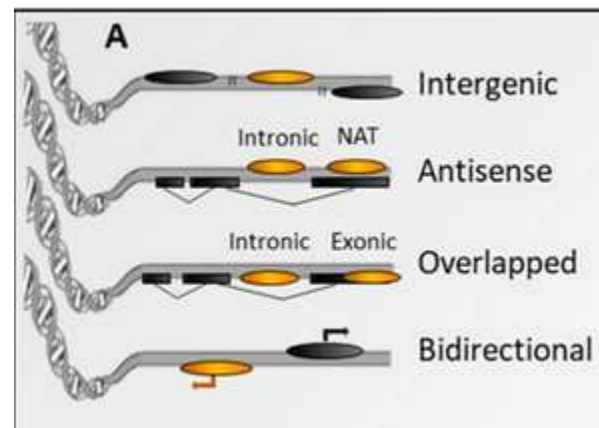
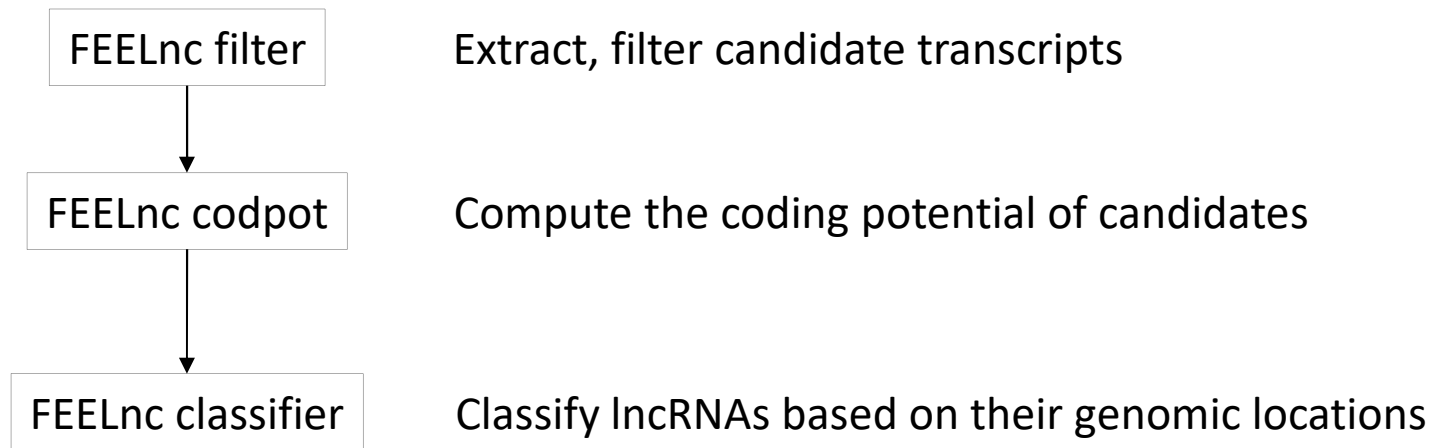
➤ Pipeline nf-core rnaseq



MONOPOLY : BLUE method

> Feelnc (prediction only !!)

<https://github.com/tderrien/FEELnc>

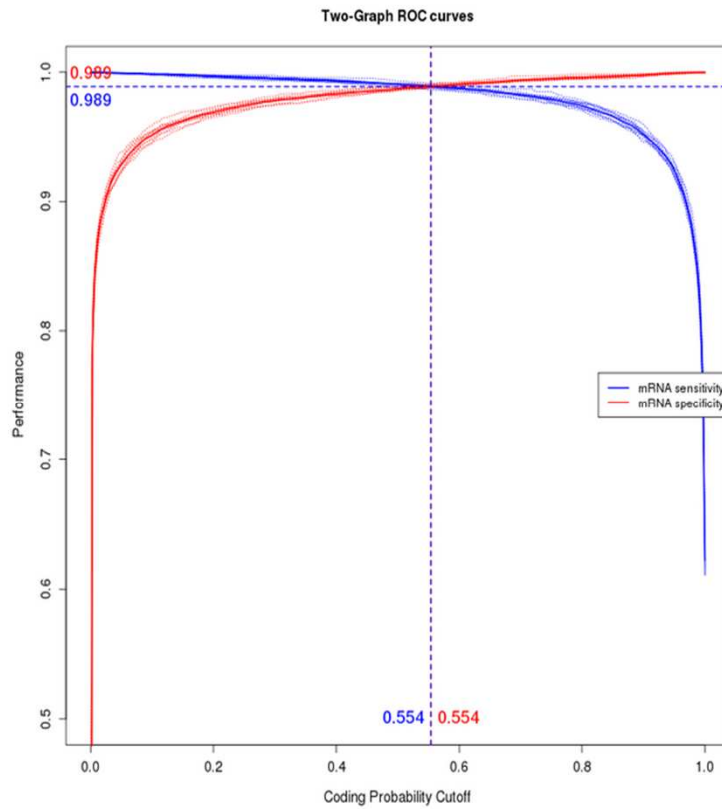


Salviano-Silva et al., 2018, *Non-coding RNA*

FEELnc Wucher et al., 2017, *NAR* p. 9

➤ Results FEELnc

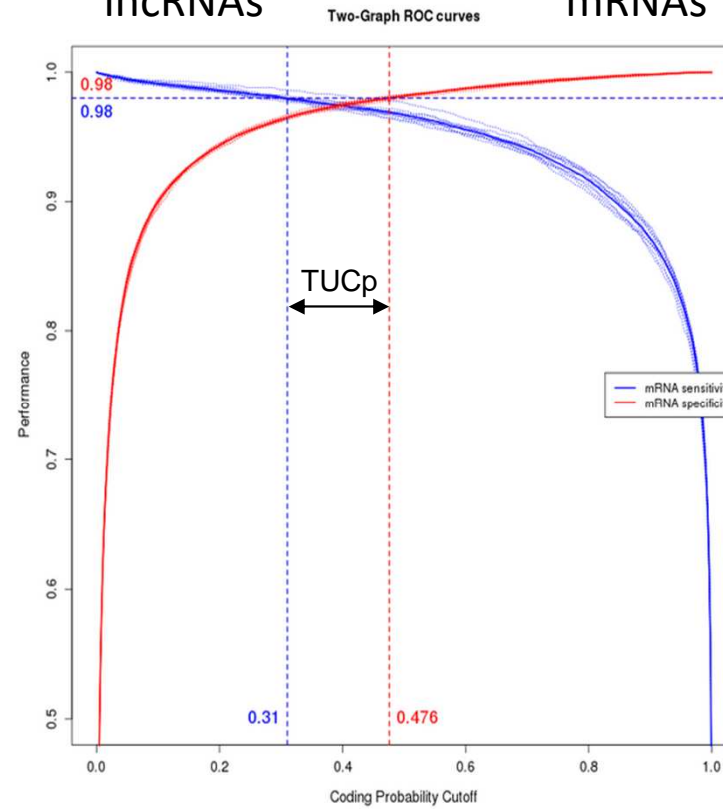
intergenic

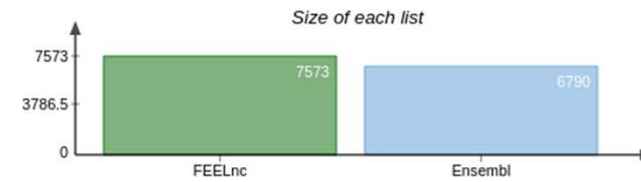
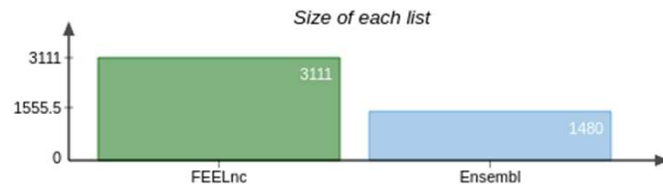
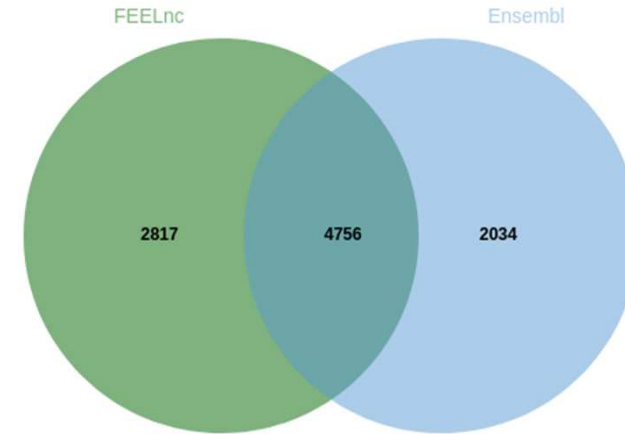
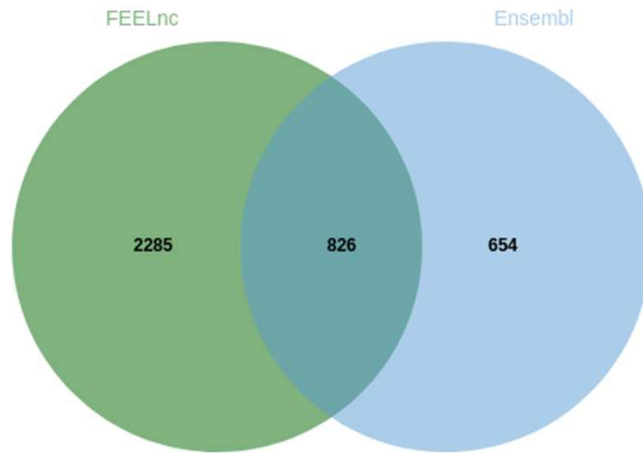


shuffle

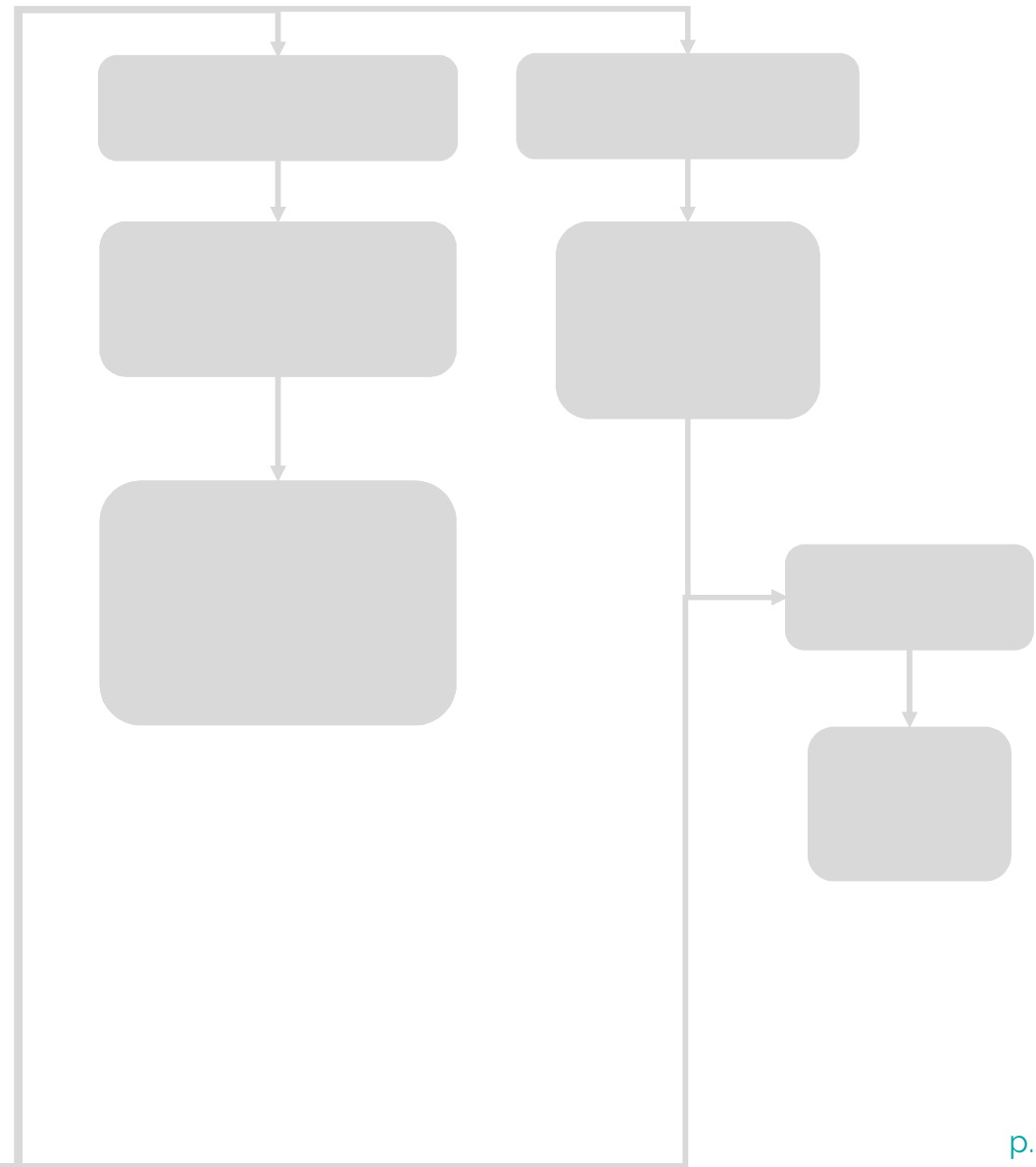
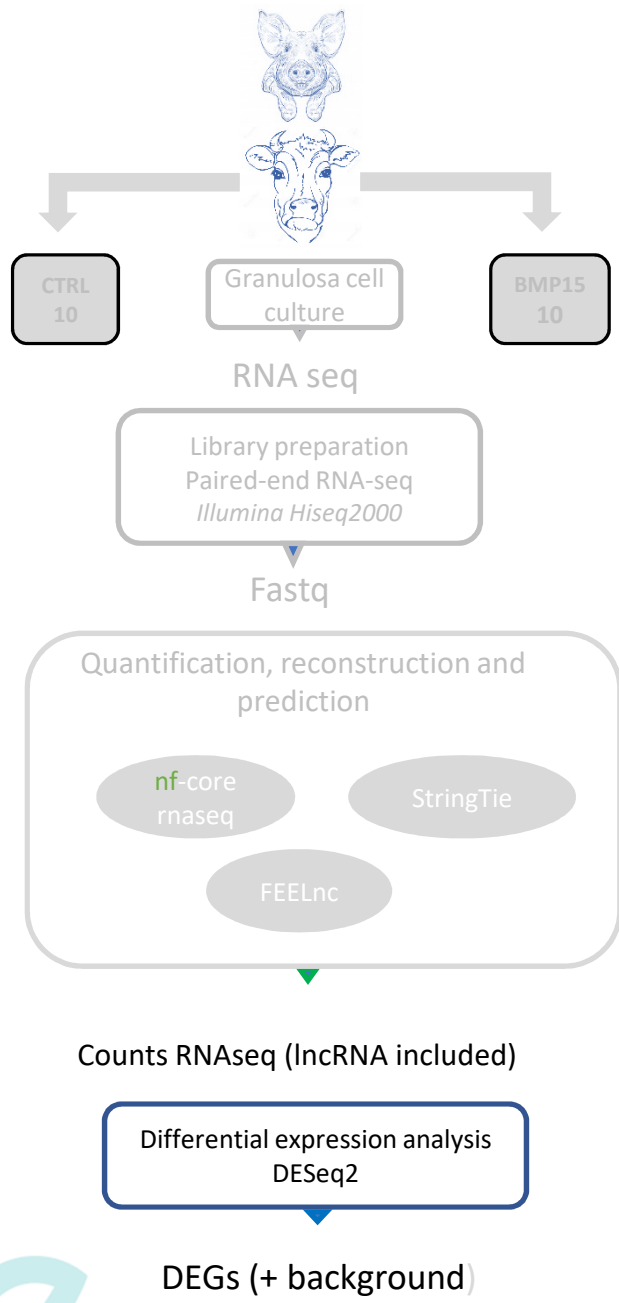
lncRNAs

mRNAs

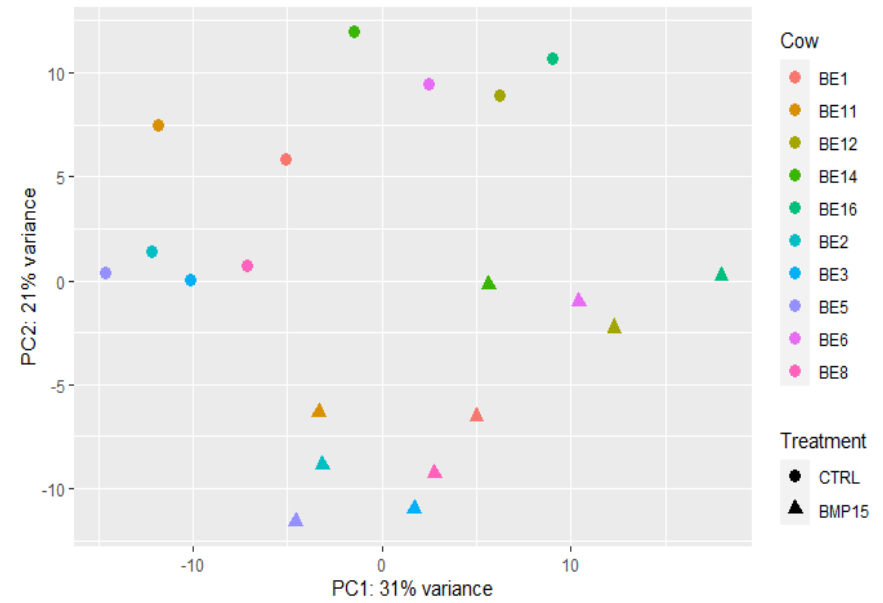
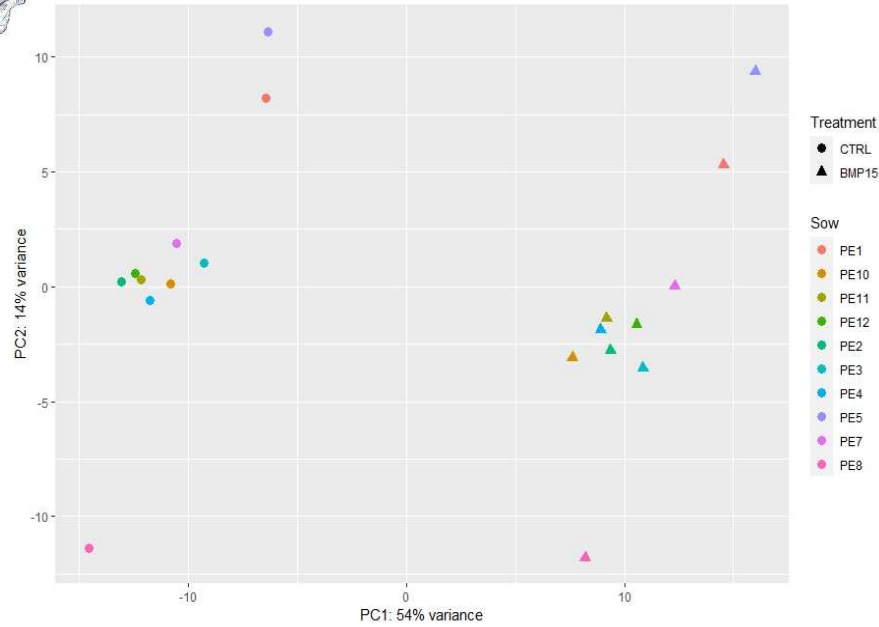




Venn diagram comparing the lncRNAs already known by ENSEMBL and those predicted by FEELnc



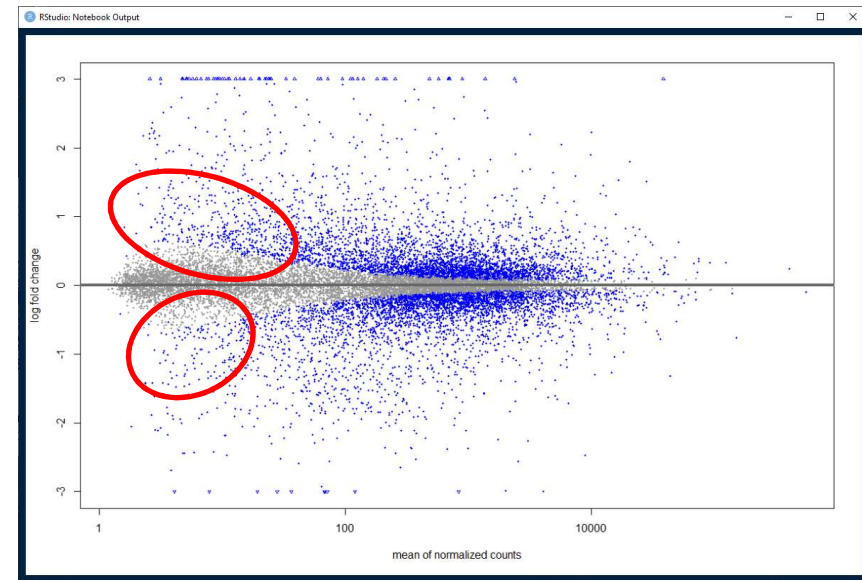
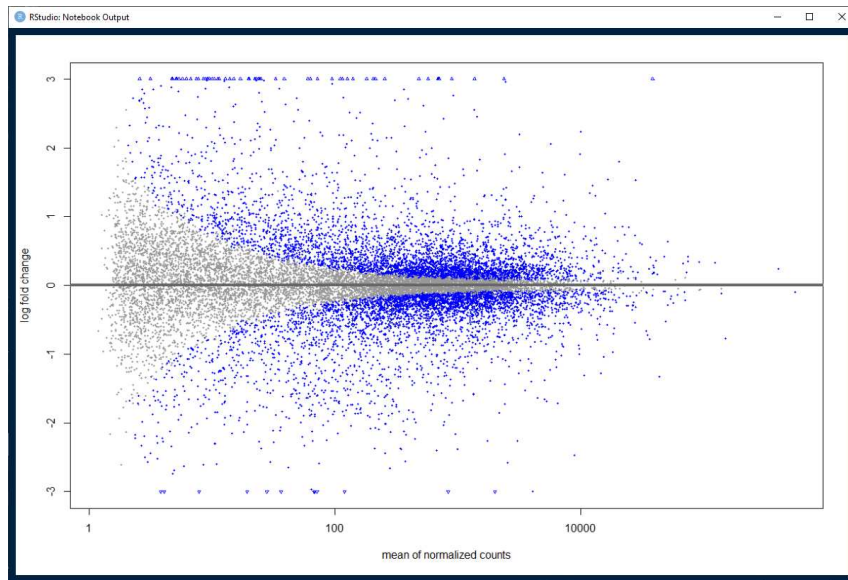
PCA : paired samples



➤ Differential analysis

DESeq2 Shrunken log₂FC, paired samples

Apeglm package



➤ Identification of DEGs



15 164 expressed genes

$(\text{rowsum}(\text{counts}(\text{dds}) > 1) > 10)$

4 521 DEGs

$\text{padj} < 0,05$

240 up ; 203 down

$\text{padj} < 0,05$ et $|\text{Log}_2\text{FC}| > 1$

443 DEGs

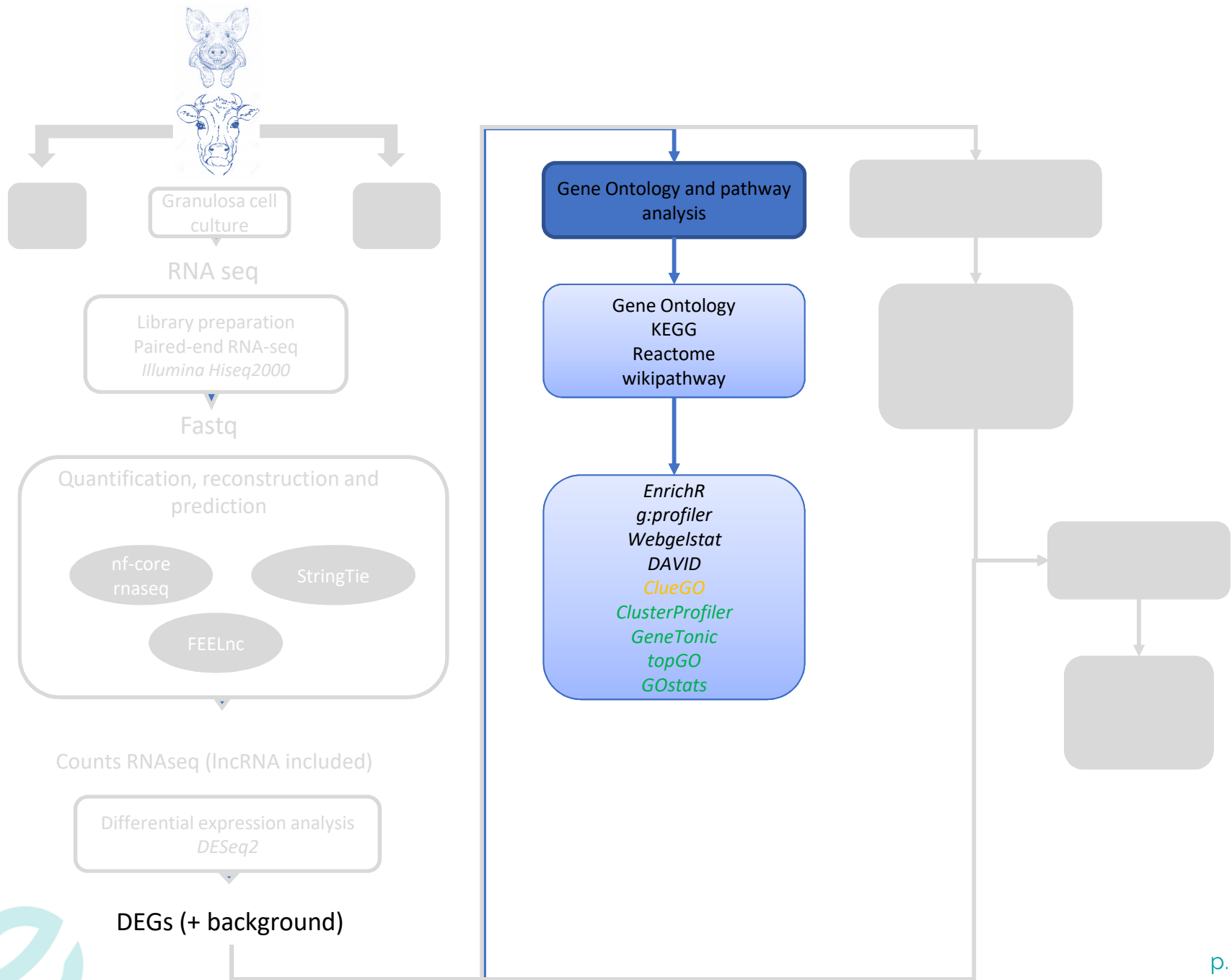


16 135 expressed genes

7 909 DEGs

487 up ; 521 down

1 008 DEGs



➤ GeneOntology – functional enrichment

ORA : Over representation analysis (input = DEGs), is based on a hypergeometric test (Fisher's exact test) (Boyle et al., 2004).

GSEA : Gene Set Enrichment Analysis (All expressed genes, ranked), is based on an enrichment score (Subramanian et al., 2005)

DAVID
EnrichR
g:profiler
Webgestat
ClueGO
GeneTonic
topGO
Gostats
ClusterProfiler

DAVID : <https://david.ncifcrf.gov/>

Enrichr: <https://amp.pharm.mssm.edu/Enrichr/>

g:profiler: <https://biit.cs.ut.ee/gprofiler/>

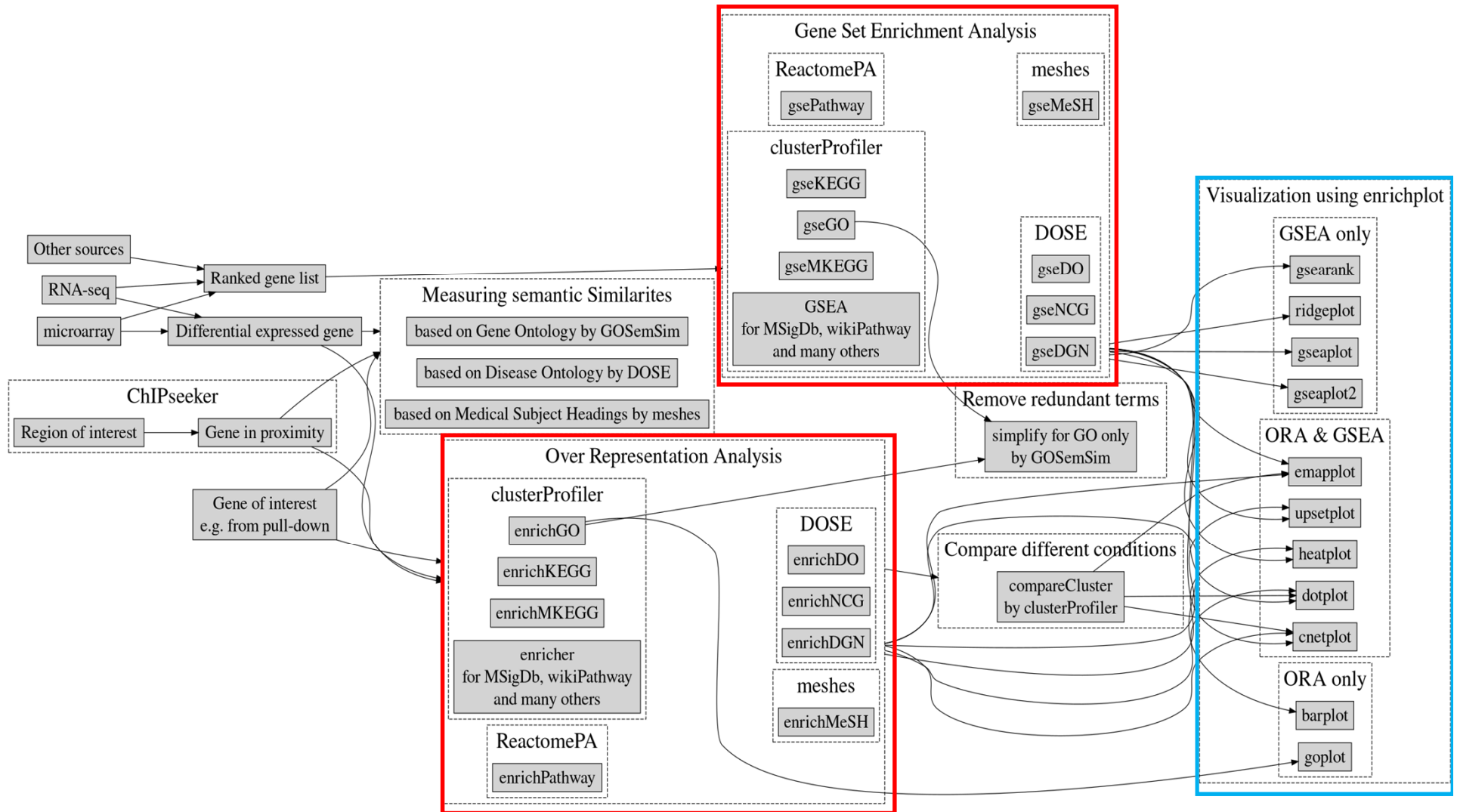
Webgestat : <http://www.webgestalt.org/>

TopGO and fgsea R packages

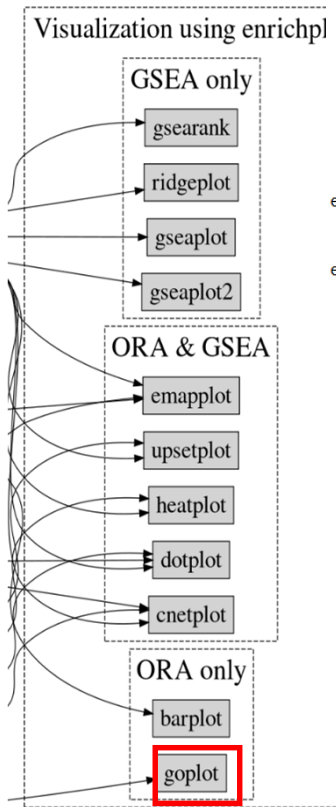
Package *GeneTonic* (Marini et al., 2021)

Package *ClusterProfiler* (Wu et al, 2021)

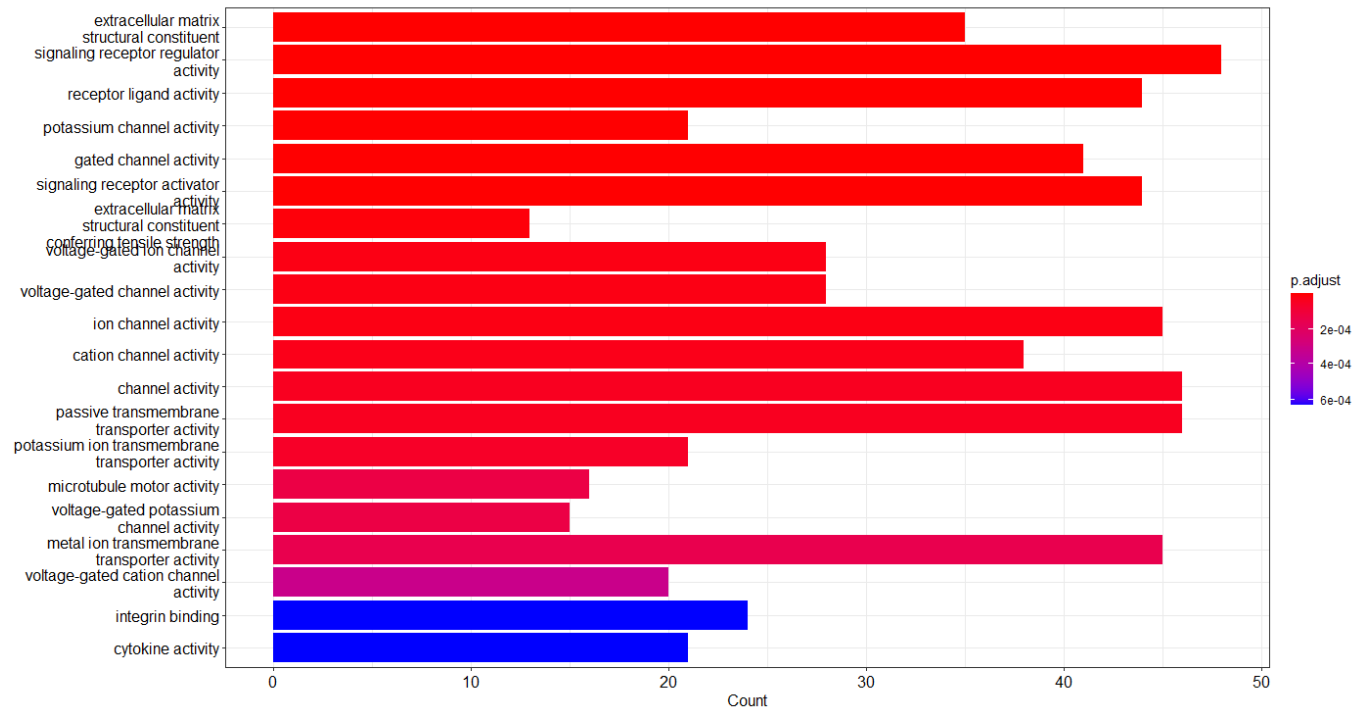
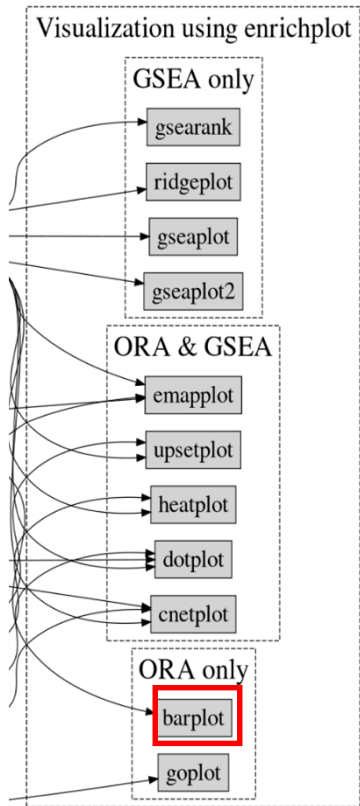
ClusterProfiler package Guangchuang Yu



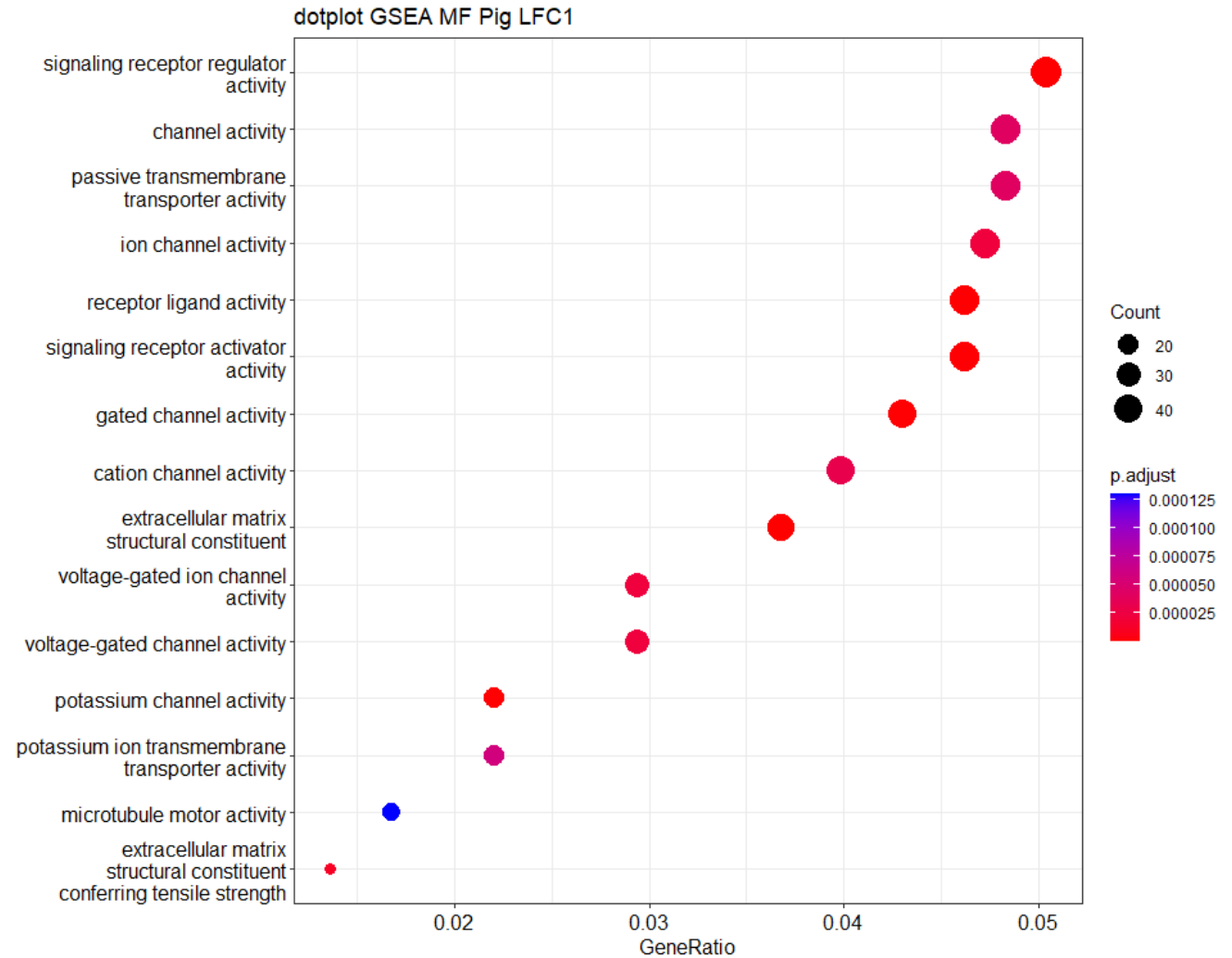
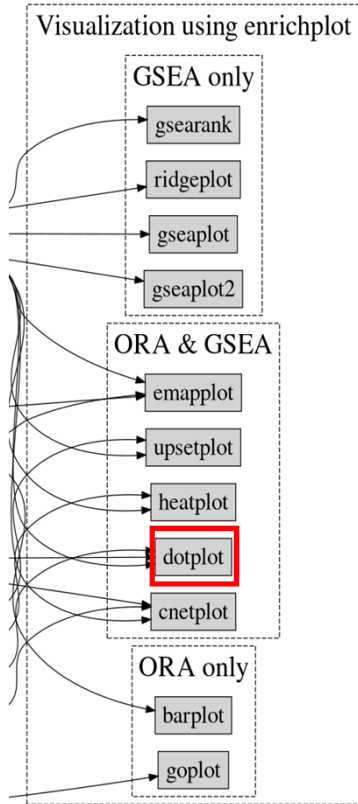
GO plot



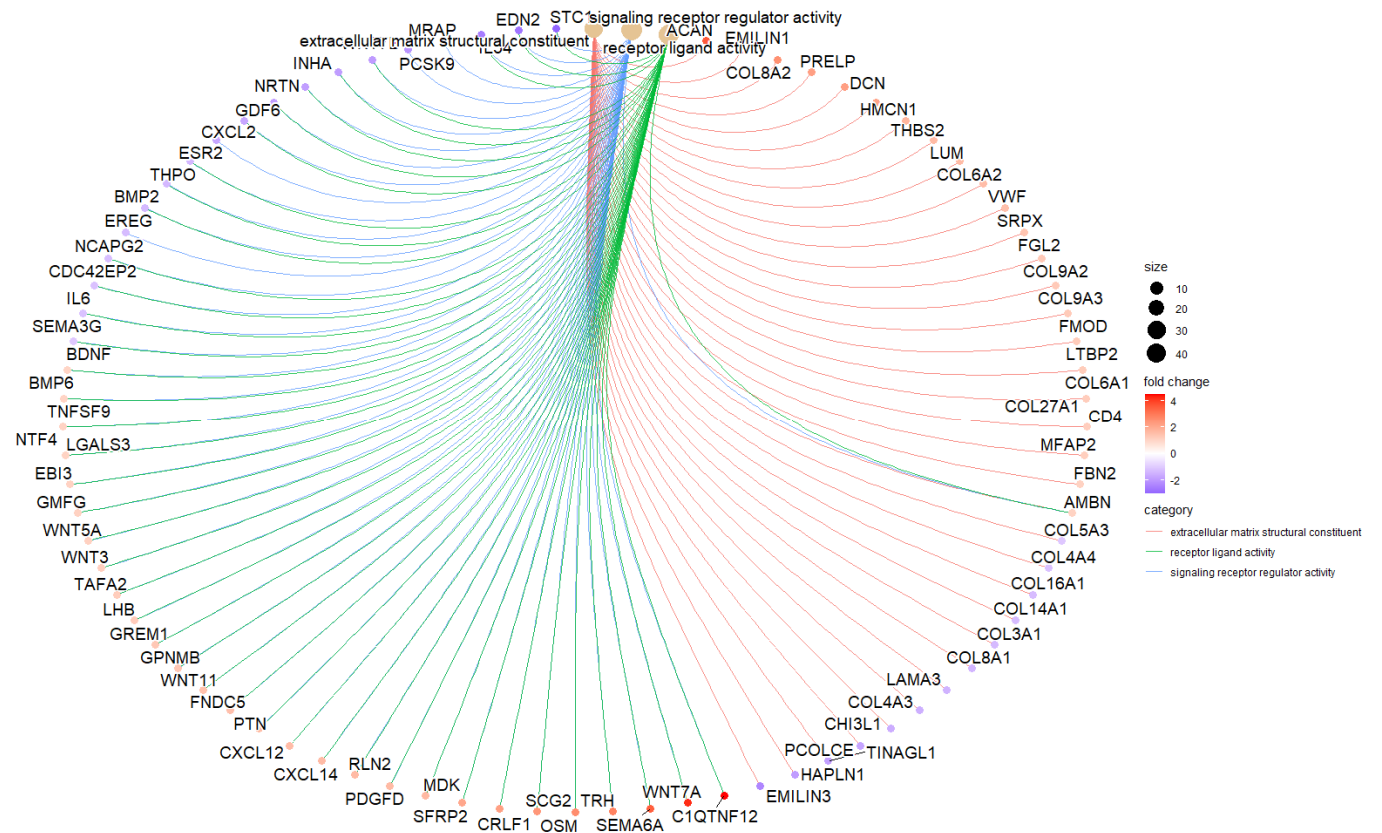
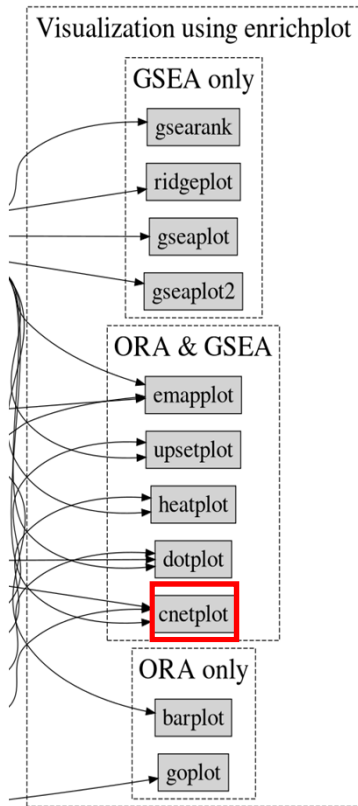
➤ Bar plot



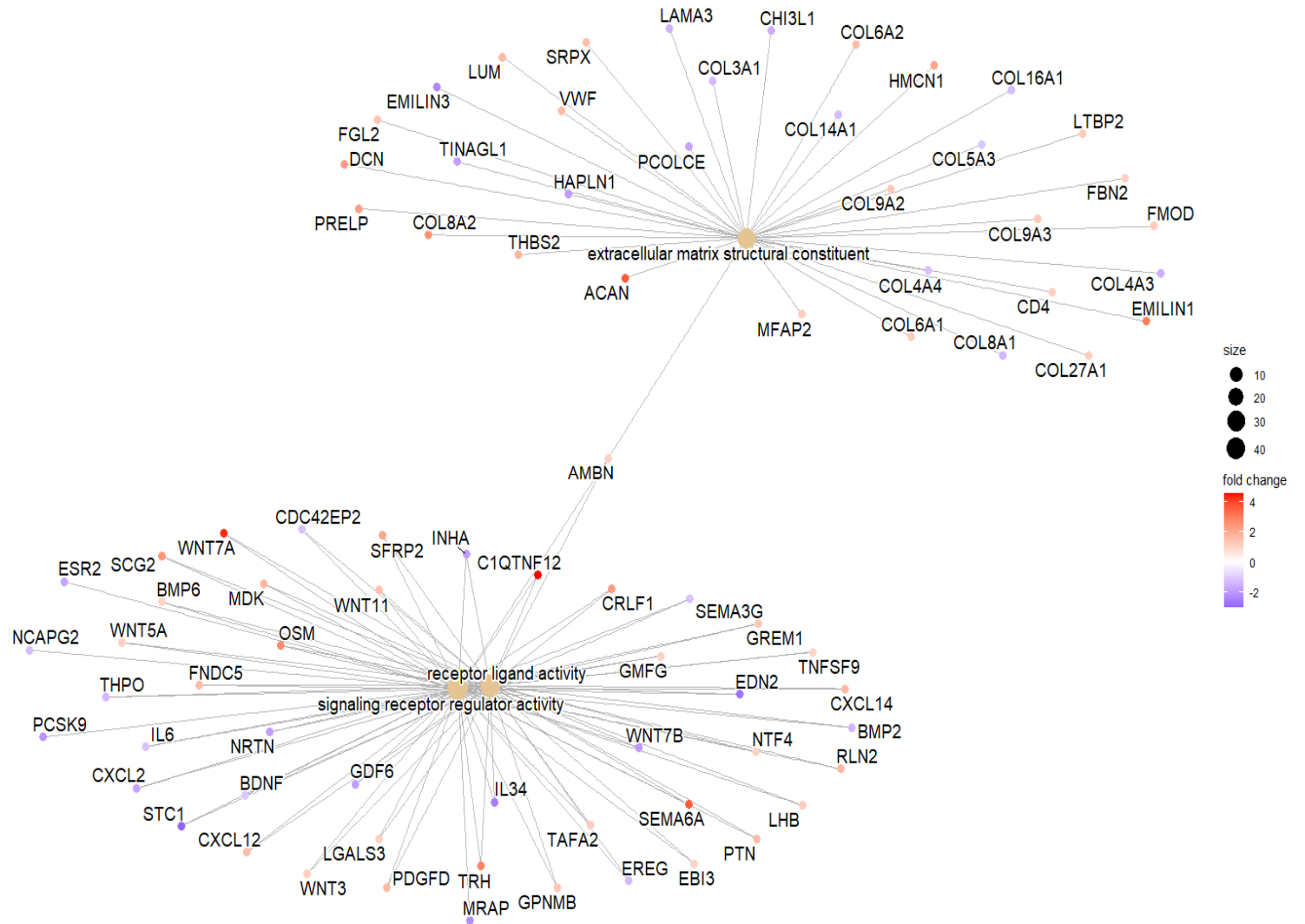
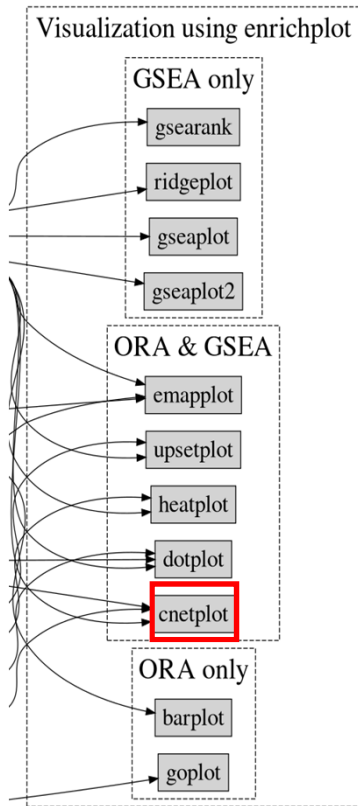
➤ Dot plot



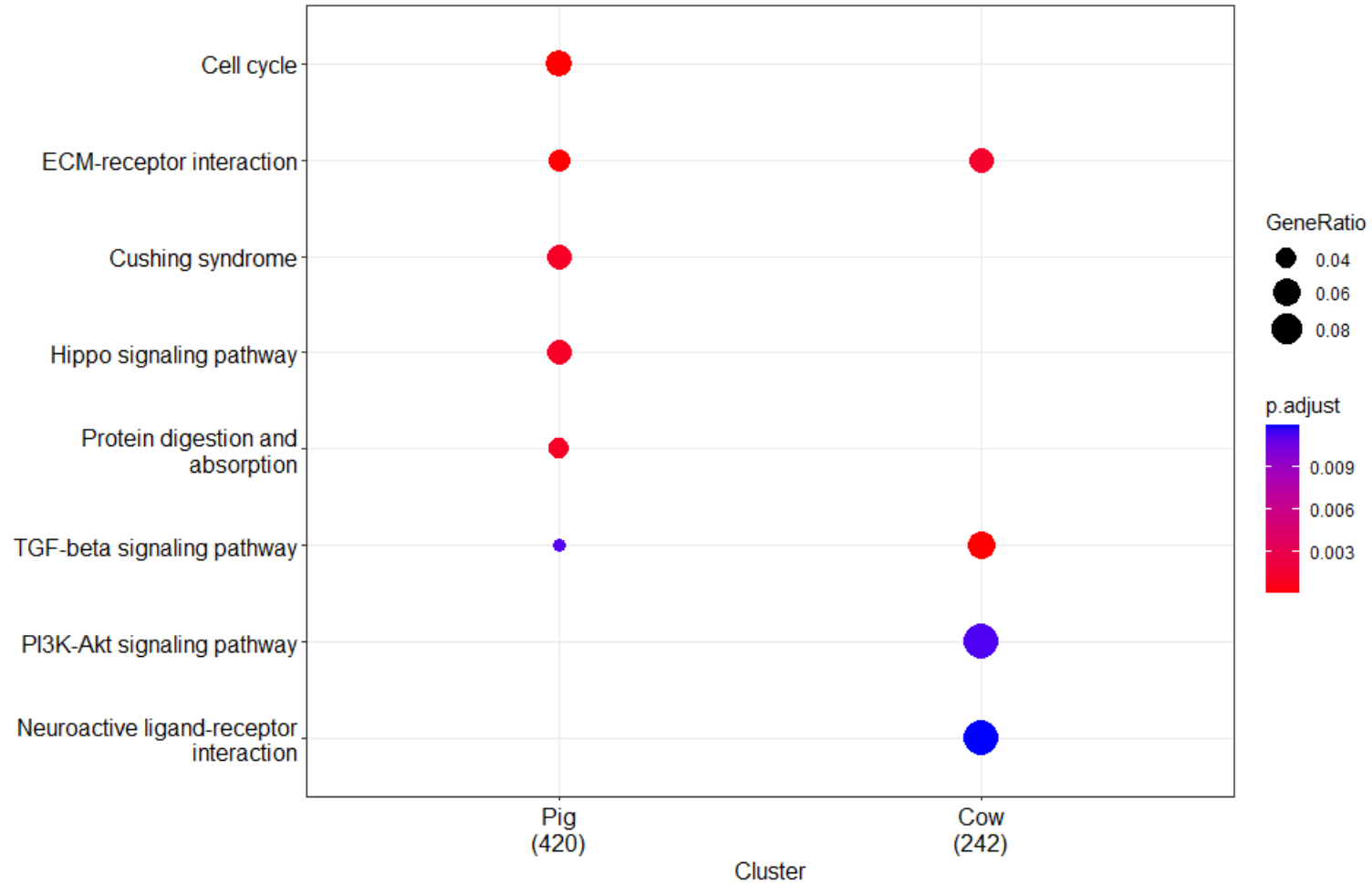
➤ Cnet plot (circular)



➤ Cnet plot



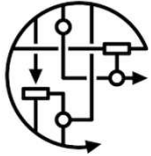
➤ Compare Cluster



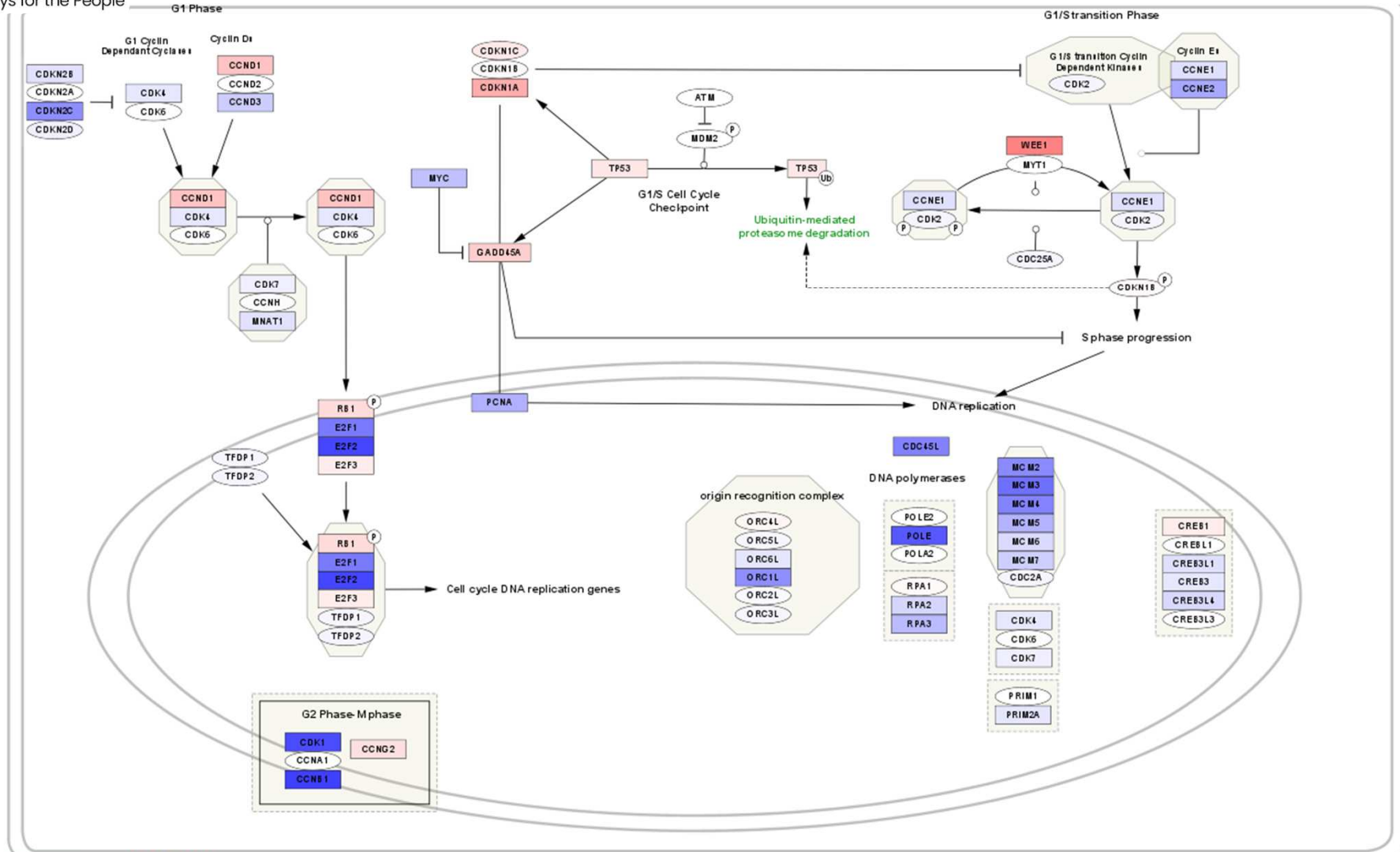
KEGG pathway

➤ Compare cluster



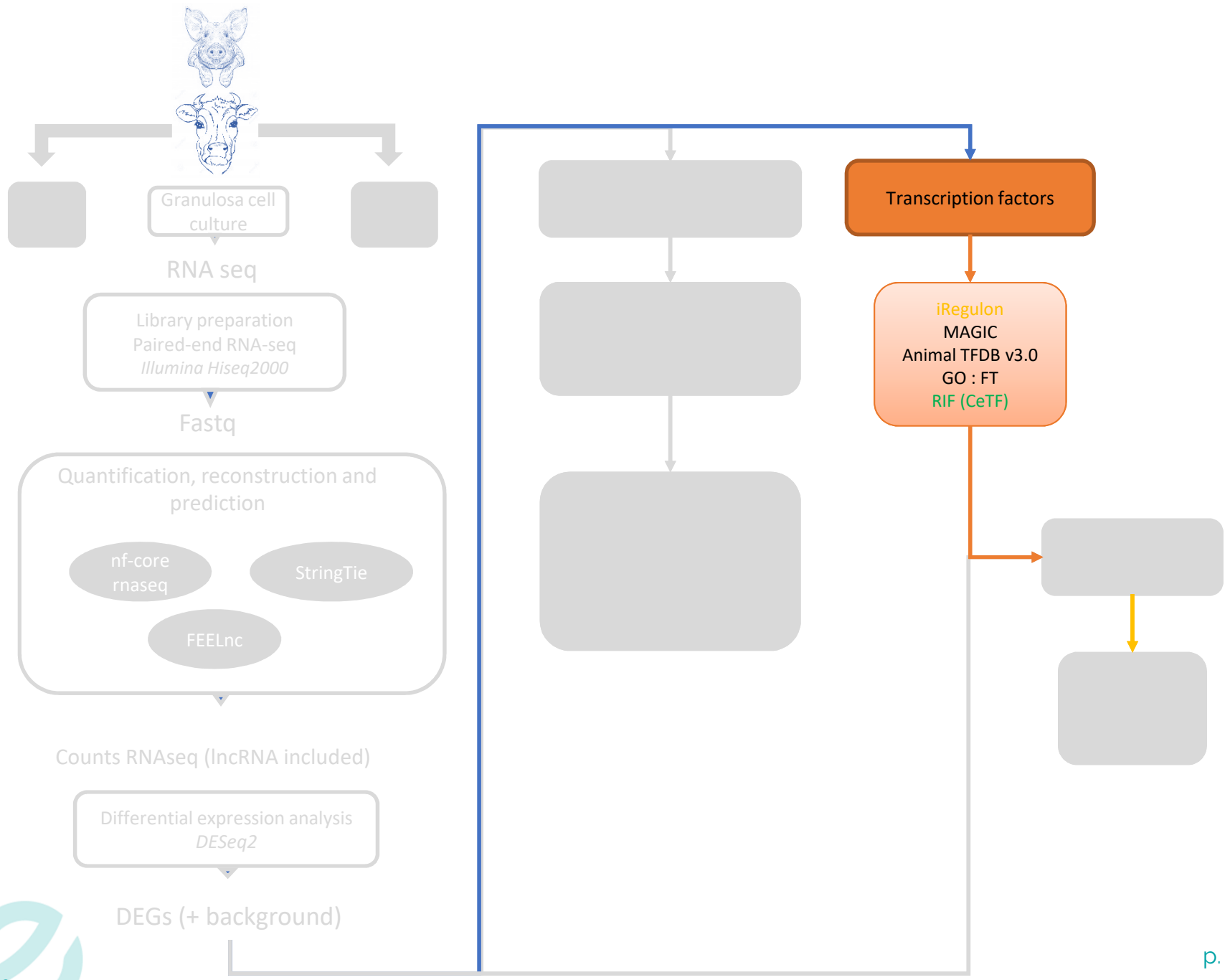


WP45 G1 to S cell cycle



Inhibition cell cycle and tissue development, inhibition cell survival; increased apoptosis





➤ Transcriptions factors :



Raw view :

iRegulon : Database de 10 000 FTs + 1 120 ChIP-seq datasets (Janky et al., 2014)



iRegulon
MAGIC
Animal TFDB v3.0
GO : FT
RIF (CeTF)

MAGIC Mining Algorithm for Genetic Controllers: 2312 ChIP-seq tracks 684 FT in 588 cell lines (ENCODE data) (Roopra 2020 *Plos Comput Biol*) (cluster)

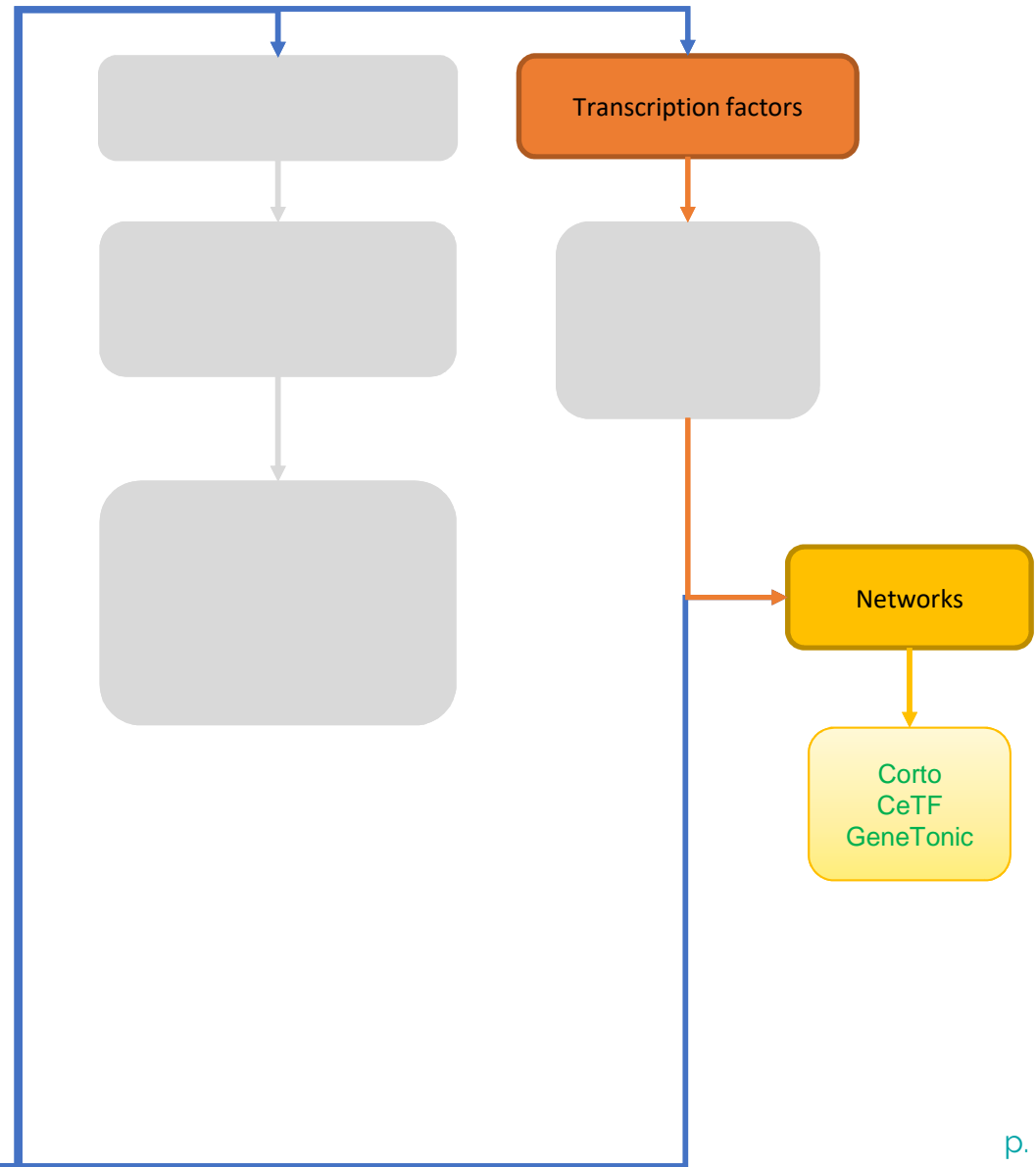
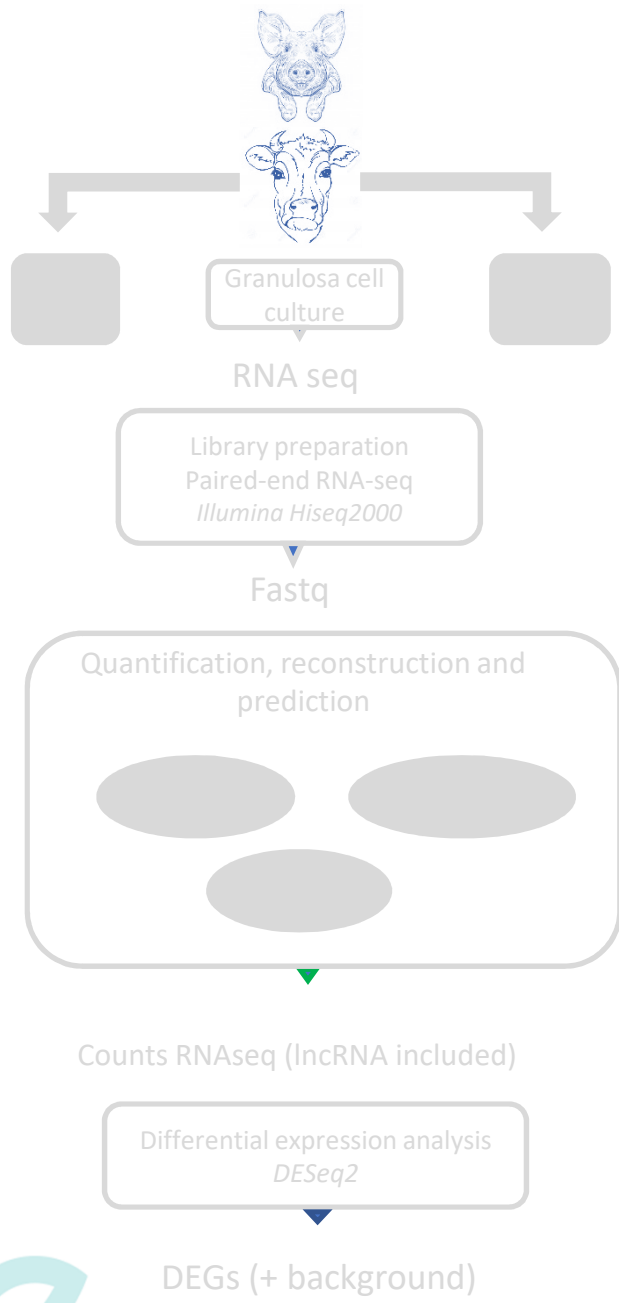
Gene Regulatory Networks (GRN) → Detailed view

Bos taurus: 1396 TFs and 935 TF Cofactors

Sus scrofa: 1490 TFs and 937 TF Cofactors



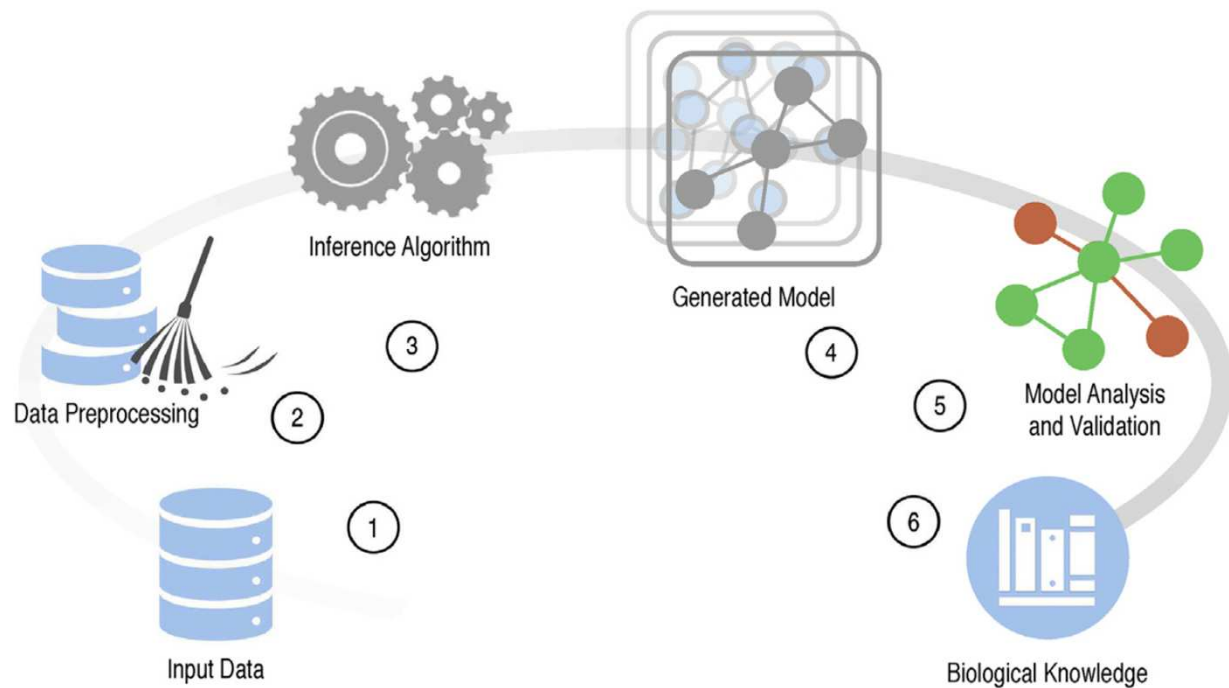
Gene Ontology : DNA-binding transcription factor activity



➤ Gene Regulatory Networks reconstruction

Several inference algorithms

- Information theory (co-expression)
- Boolean networks
- Differential equations models
- Bayesian models
- Neural models



➤ PCIT approach : Partial Correlation with Information Theory

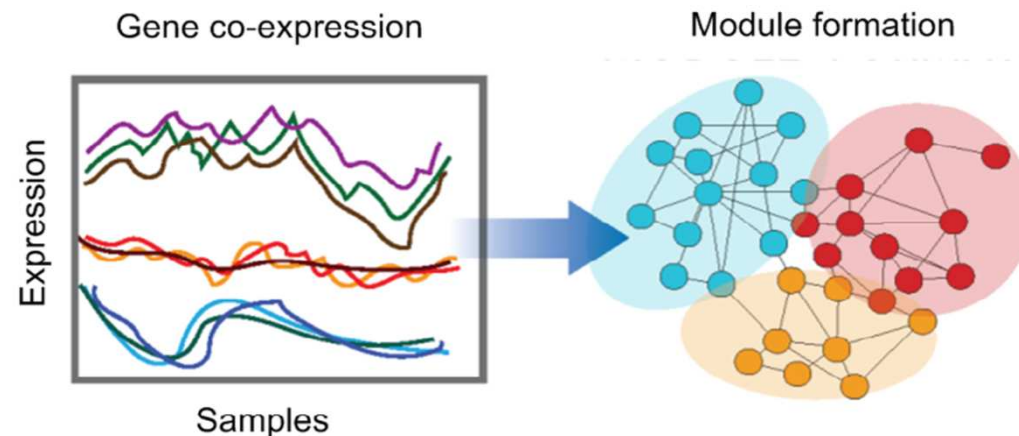
For every trio of genes in x , y and z

- 1) The three first-order partial correlation coefficients are computed -> the strength of the linear relationship between x and y that is independent of (uncorrelated with) z .

Obtention d'un seuil « local » pour capturer les associations significatives

- 2) Data Processing Inequality (DPI) or theorem of Information Theory which states that 'no clever manipulation of the data can improve the inference that can be made from the data' (Cover and Thomas 2012)

Packages R **CeTF**, **Corto**



➤ Package CeTF : identification of crucial FTs

RIF Regulatory Information Factors algorithm (Reverter et al., 2010 *Bioinformatics*) → MSTN

Counts normalisés de DEGs

Cibles

Liste de FTs

Régulateurs

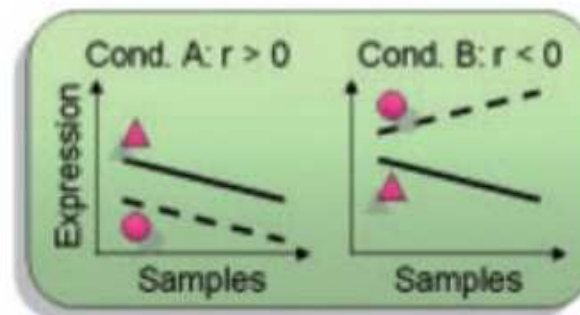


Calcul de la corrélation de la co-expression de chaque TF avec les DEGs pour les 2 conditions

RIF1: high score to TFs that are most differentially co-expressed, highly abundant.

High RIF1 = FTs « constants »

RIF2: high score to TFs whose expression can predict better the abundance of DEGs



➤ RIF Results

TF	avgexpr	RIF1	RIF2
RARG	4.4308315	-2.362989	-0.4269886
STAT2	5.5116914	2.347202	0.3046848
CIB1	6.4784370	-2.079084	0.4312936
RORA	2.8853325	-1.983128	-0.2532182
MALT1	5.3576710	3.138360	-0.5968538
CREB3	5.9433637	-2.617405	0.3039166
HEY1	0.6291504	2.012688	0.4760702
COP55	5.9009044	2.583354	-1.1730226
ATF6	8.2596171	2.067810	-0.6565662
GATA5	0.5430692	2.918902	0.4725577

26 TFs RIF1

	TF	avgexpr	RIF1	RIF2
1	ZNF423	5.261707	3.43867	-1.28137

TF	avgexpr	RIF1	RIF2
ELK4	5.9506900	5.0683310	-3.121338
DLX2	1.4871928	0.8961663	-2.845057
ZNF35	3.4982397	1.6921604	-2.709549
TICAM1	4.4586161	0.8491830	-2.689220
FEZF2	0.2689711	-0.5681378	-2.648282
UFL1	6.2945395	1.5768689	-2.400373
SP7	2.4673947	2.3311699	-2.390159
KLF13	7.9588770	-0.3132815	-2.286667
ZHX3	5.3036326	-0.5644726	-2.175302
RARA	6.1011870	2.5207260	-2.148701

29 TFs RIF2

	TF	avgexpr	RIF1	RIF2
1	NTRK1	3.732381	1.2677245	1.807717
2	LRRC7	2.767650	0.0279897	-1.881063
3	ARNTL2	6.167500	-0.4328875	1.866842

Packages R CeTF



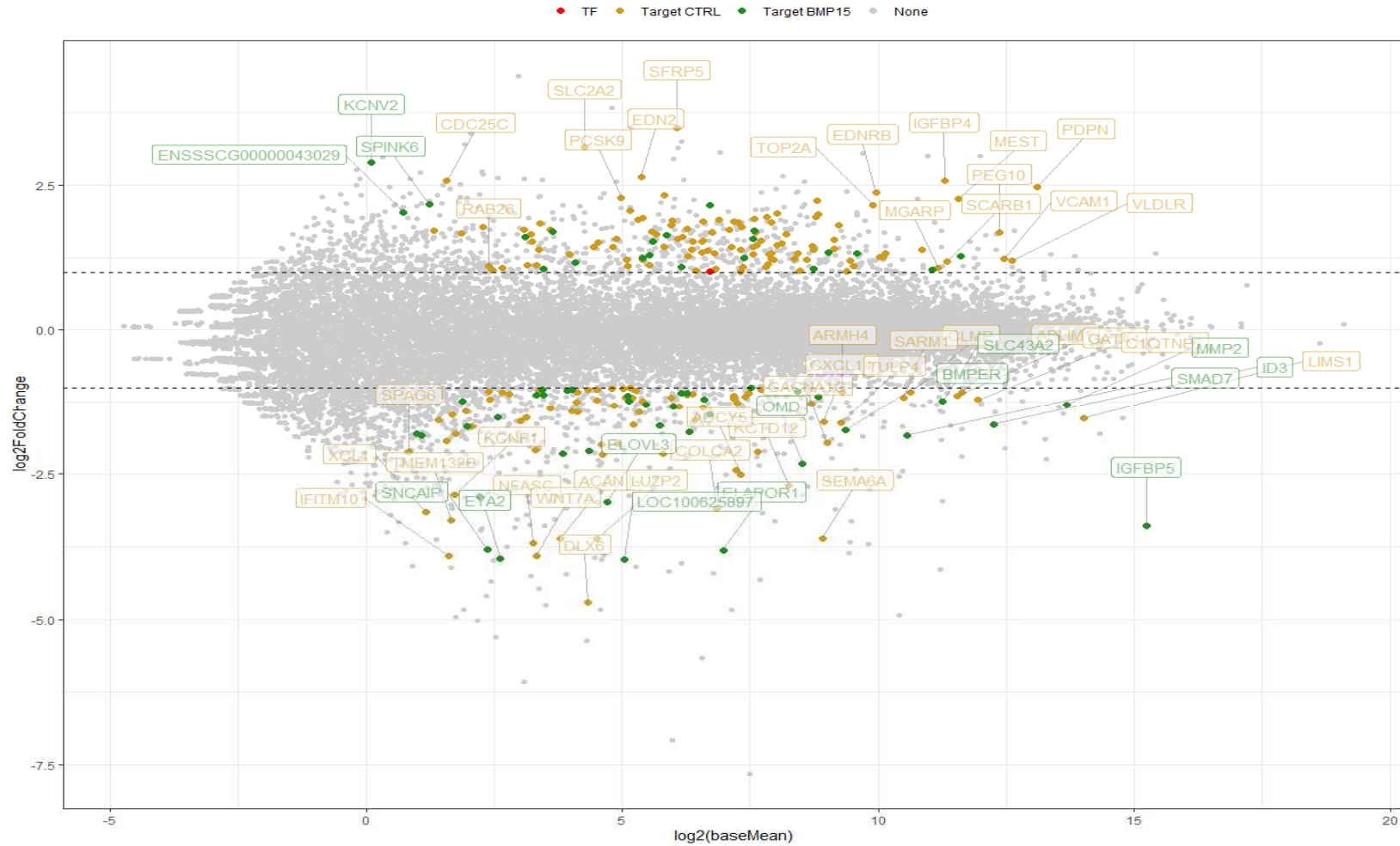
Zscore 1,96 pval<0,05

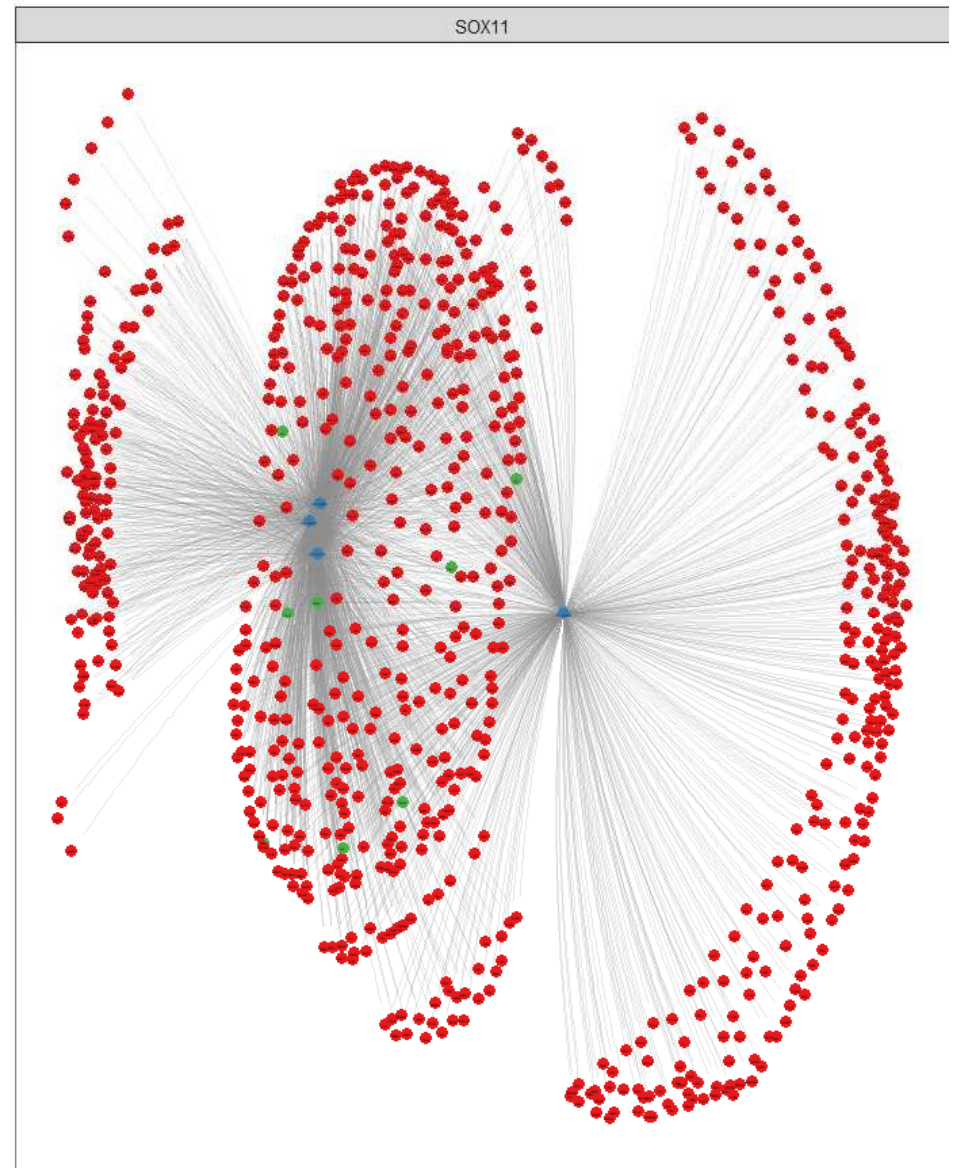
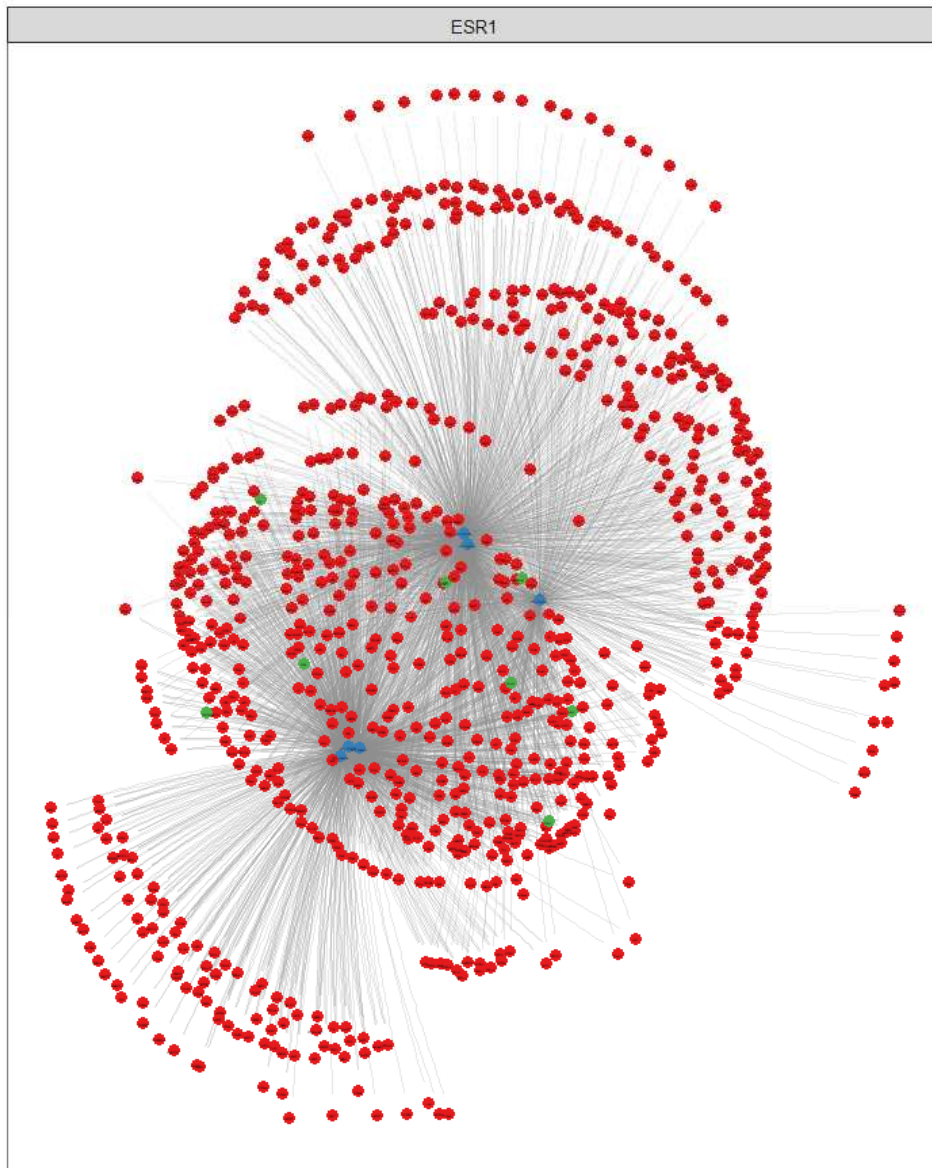


Zscore 1,65 pval<0,10

➤ FT ESR1 and its targets

Smear Plot for ESR1 and its targets





Type ● gene ● pathway ● TF

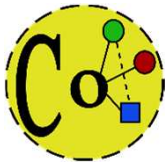
➤ Package CeTF : Pros and cons



RIF algorithm in R



2 conditions, little used, maintainer not responding, graphic interface.



Corto : (Correlation Tool): an R package to generate correlation-based DPI networks. Mercatelli et al., 2020 Bioinformatics



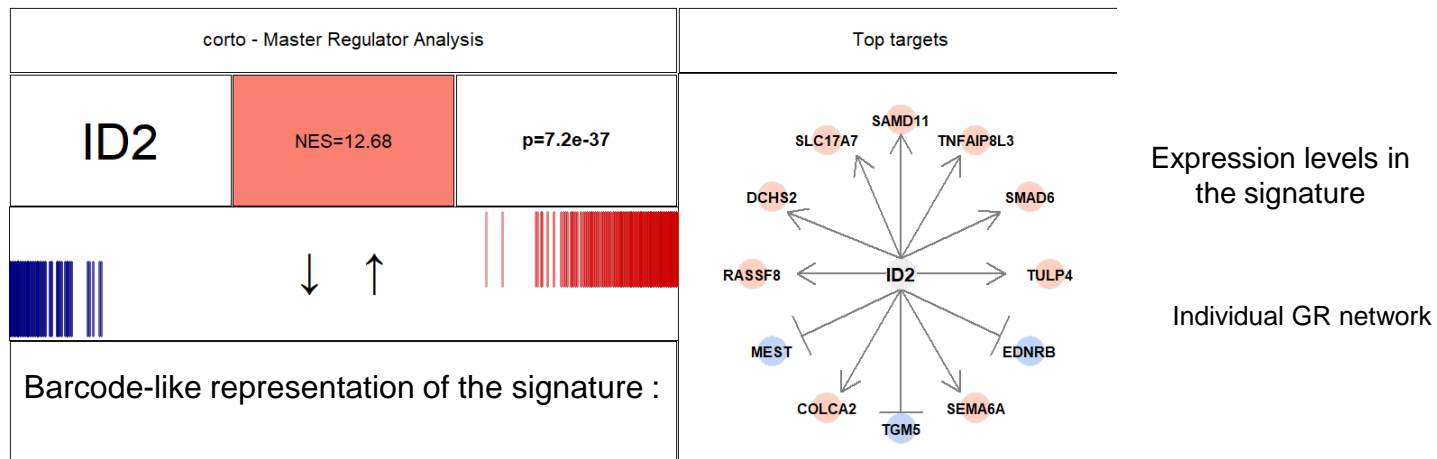
Maintainer ++

1) Identification of TFs expressed in the dataset

```
[1] "FOXM1" "E2F7" "TCF19" "E2F1" "MYBL2" "E2F8" "ZNF367"
[8] "ZNF704" "SMAD7" "PRRX2" "ATOH8" "DLX2" "TBX2" "SP7"
[15] "DRGX" "DLX5" "ID3" "NR5A2" "HIVEP1" "NFIB" "ZNF182"
[22] "TEAD4" "RTKN2" "SFRP5" "GATA5" "ID2" "SOX11" "PBX4"
[29] "GATA4" "ID1" "E2F2" "MYOCD" "RGCC" "ZFH4" "DLX3"
[36] "VDR" "ZBTB16" "DLX6" "NR4A1" "ADCY8" "HAND2" "SNAI2"
[43] "SHOX2" "ATF3" "TRAIP" "ZNF423" "WNT5A" "TCF7" "ESR2"
[50] "EN1" "SOX9" "MKX" "THRB" "MYCN" "MSX2" "NKX2-8"
```

2) Gene network inference (optimized pairwise correlation, DPI and bootstrapping)

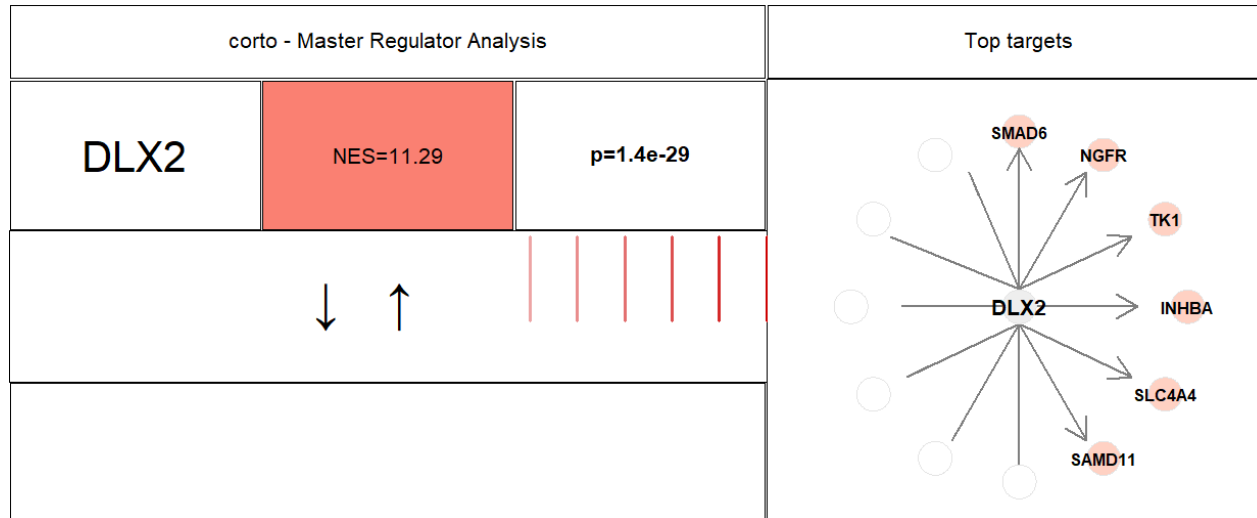
Master Regulator Analysis : TF networks vs a signature (= 2 gene expression matrices)



Expression levels in the signature

Individual GR network

corresponding P value (based on 10 000 permutation tests and signature sample shuffling)



The transparency of each bar is associated to the value of the target in the signature.

➤ What else ?

- From R to Cytoscape or Gephi :

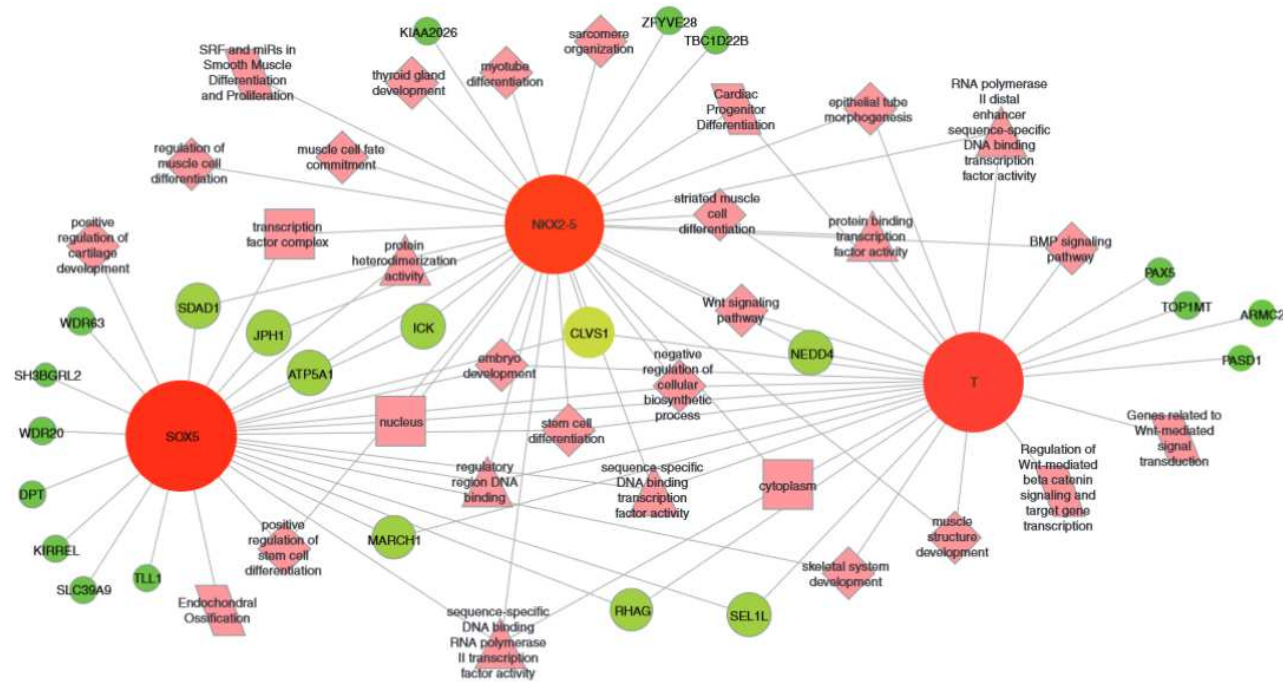


Fig. 3. Transcription factors network. Transcription factors (in red), with related genes (green), pathways (parallelogram) and gene ontology: molecular functions (triangle), biological process (diamond) and cellular component (rectangle).

- Add lncRNAs : Test TAGADA pipeline

➤ Perspectives : TAGADA pipeline (GeneSwitch project)

Another pipeline using Nextflow for count matrix generation and lncRNA prediction

	Nextflow nf-core rnaseq + FEELnc + StringTie	Nextflow TAGADA
Quantification	RSEM	Stringtie
Merge of GTFs by sample	Outside, StringTie Merge	Inside, T-merge
transcript quantification	Outside, Stringtie	Inside, Stringtie
lncRNA prediction	Outside, FEELnc Choice of the method intra WF	Inside, FEELnc Choice of the methode upstream WF

+ Filters on transcripts « de novo » are also different.


> What else ?

- GRN with lncRNAs
- Use co-expression networks to identify potential trans-targeted genes.
- Validate the trans target with lncTar (Li et al., 2014, *brief. Bioinform*) :
Predict lncRNA-RNA interactions based on secondary structure

> Thanks

TAGADA pipeline

Sarah Djebali  **Inserm**

Cervin Guyomar 

Cyril Kurylo

Sylvain Foissac

