

#### Valorisations of epigenomic and transcriptomic data Guillaume Devailly

#### ▶ To cite this version:

Guillaume Devailly. Valorisations of epigenomic and transcriptomic data. Animation scientifique d'Unité, Dec 2017, Toulouse, France. hal-01800387

#### HAL Id: hal-01800387 https://hal.science/hal-01800387

Submitted on 4 Jun2020

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers. L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License





## Valorisations of epigenomic and transcriptomic data

**Guillaume Devailly** 







Transcriptionnal regulation: a 2-slides introduction

- MBD2, a major DNA methylation reader
- Heat\*seq web app:

http://www.heatstarseq.roslin.ed.ac.uk/

Functionnal annotation transfert using co-

expression networks



Epigenomics and the human transcript diversity





- \* Same genome
- Distinct cellular phenotypes
- Differential gene expression
- Cellular environment +

epigenetics













## MBD2 binding dynamics during oncogenic transformation

**PhD at the Cancer Research Center of Lyon** Supervisor: Robert Dante Patrick Mehlen's team







 $\mathsf{V}$ 



#### **3- Erase**

- ShmC TET + BER
- BER / NER / MMR
- passive demethylation







#### UHRF family UHRF UHRF 1 2











**SCIENCE & IMPACT** 

.09 2017-<u>12-19</u>

## MBD2 ChIPseq validation 1/3:





CDH13

## MBD2 ChIPseq validation 2/3:









#### Endogenous MBD2 binds methylated DNA *in vivo*

Almost all MBD2 binding sites are methylated പ 👝 🗠  $\geq 2$ 2 p e a K > 78% of peaks are 7 9 W 9 T 9 C 7 methylate d 5Kb ↔ 5Kb Read density HMLER



# Endogenous MBD2 binds methylated DNAAlmost all<br/>MBD2 binding1/4th of<br/>methylated DNAMBD2 binding<br/>depends on

their

methylation

levels



## Endogenous MBD2 is a DNA methylation dependent transcriptional



## MBD2 is a DNA methylation dependent transcriptional repressor









HMLER

2164 genes up by <mark>siMBD2</mark>

70% also up by DAC

667 genes down by siMBD2 40% also up down DAC



3510 genes up by DAC

43% also up by siMBD2



## Redistribution of MBD2 during oncogenic transformation: example of *CLDN6/TNFRSF12A*





Transcription level (RNAseq)

> Relative transcription level



siMB

siCtrl

DAC, p<0.01

### Conclusions & Perspectives

- MBD2 is a major reader of DNA methylation, at least in studied cell lines.
- MBD2 is redistributed during oncogenic transformation. This redistribution plays role in the transcriptome modifications of transformed cell lines.
- What are the mechanism implicated in the redistribution of MBD2?
- Does targeting MBD2 reduces the transformed phenotype?

#### http://ngs-qc.org/navi/index.php

Accession	\$ Organism	\$ Sample	\$ Experiment	\$ Mapped Reads	QC stamp	
GSM1544114 🔗	Homo sapiens	N/A	MBD2 ChIP-seq	57,009,909	BBB	0
GSM1544111 🔗	Homo sapiens	N/A	MBD2 ChIP-seq	57,767,880	BBB	0
GSM972973 🔗	Mus musculus	ESC, stem cell	MBD2 ChIP-seq	28,211,050	ССВ	0
GSM2534656 🔗	Homo sapiens	immortalized cell	MBD2 ChIP-seq	23,401,218	ссс	0
GSM1322266 🔗	Homo sapiens	N/A	MBD2 ChIP-seq	32,869,475	ссс	0
GSM972994 🔗	Mus musculus	ESC, stem cell	MBD2 ChIP-seq	19,671,342	CDD	0
GSM2527610 🔗	Homo sapiens	K-562	MBD2 ChIP-seq	23,414,725	CDD	0
GSM1388122 🔗	Homo sapiens	N/A	MBD2 ChIP-seq	27,212,212	DCC	0
GSM972978 🔗	Mus musculus	N/A	MBD2 ChIP-seq	25,225,988	DCC	0
GSM2527611 🔗	Homo sapiens	K-562	MBD2 ChIP-seq	27,605,362	DCC	0
GSM1077269 🔗	Mus musculus	ESC, stem cell	MBD2 ChIP-seq	27,360,560	DDC	0
GSM1006707 &	Homo sapiens	HeLa	MBD2-V5 ChIP- seq	10,943,628	DDD	0

#### Thanks



Robert Dante Mélodie Grandin Pauline Mathot Véronique Corset Catherine Guy Solène Le Guervenel Duygu Ozmadenci Laury Perriaud Anne-Pierre Morel Patrick Mehlen

#### Collaborators



CNRS UMR7216, Université Paris 7

Pierre-Antoine Defossez Olivier Kirsh Benoit Miotto Audrey Roussel-Gervais







## ROSLIN Heat\*seq

## Compare your HTSChIP-seCAGECAGEAnagha Joshi's group, The Roslin Institute, University

#### RNA-seq ChIP-seœlatasets CAGE in











### Heat\*Seq

ROSLIN

HTS is cheap Big public datasets

Genome-wide comparison is challenging







### Workflow

 1- Visit website: ww.heatstarseq.roslin.ed.ac.uk
2- Select \_\_\_\_\_\_ 3-Upload dataset \_\_\_\_\_ processed data

4- Explore

0.25

0.5

0.75





brain GSM1020640 0.9374279

0.9375823

Pearson correlation coefficient: 0.9497 Spearman correlation coefficient: 0.902

### Datasets

A	Detect	Organiam	Number of
Assay	Dalasel	Organishi	experiment S
RNA-seq	Bgee	human	77
		mouse	109
	Blueprint epigenome	human	163
	ENCODE	human	302
		mouse	192
	Roadmap Epigenomics	human	57
	Flybase	drosophil a	124
	GTEx	human	8555
TF ChIP- seq	ENCODE	human	690
		mouse	156
	CODEX	human	238
		mouse	651
	modENCODE	drosophil a	85







### HeatRNAseq

ROSLN

#### Expression



### HeatChIPseq

## ROSLN

Binary peak														
	Coordinates atri (~700.000 non overlapping regions)	X Exp 1	Exp 2	Exp 3		Exp 690								
	chr1:10073-10413	F	Т	F		F								
	chr1:16110-16390	F	F	Т		т								
	chr1:29198-29688	F	F	F		F								
									С	orre	latio	n		
	chrY:28709160- 28709494	т	Т	F				١	Exp 1	iækri: 2	X Exp 3		Exp 690	
							I	Exp 1	1	0.05 9	0.78 6		0.03 5	
			Clu	uster	ed		ł	Exp 2	0.05 9	1	0.05 8		0.11 8	
			he	a <mark>tma</mark>	р		I	Exp 3	0.78 6	0.05 8	1		0.04 7	
								·				1		
				N BAGA					0.03 5	0.11 8	0.04 7		1	SRC

## File format

ROSLN

CAGE

HeatCAGEseq

### Tab-delimited text ChiP-seq

HeatChIPseq

#### RNA-seq

HeatRNAseq







## File format

ROSLIN

	Tab-c	lelimi	ted te	ext			
RNA-seq		ChiP-s	eq		CAGE		
HeatRNAseq		HeatChlF	Pseq		HeatCAGEseq		
	chr	start	end				
	chr1	125423	125891				
	chr1	854503 2	854625 4				
	chr4	452369 8	452478 5				
	chr12	854120	854870				
	chrX	245875 0	<b>245987</b> Same g	genome v	ersion		
			thar	h the data	set		





## File format

ROSLN

RNA-seq		C	hIP-seq		C			
HeatRNAseq	HeatChIPseq				HeatCAGEseq			
	cł	٦r	start	end	name	rpm	stran d	
	cł	nr2	25486325	25486487	CAGEpeak _1	458.1 2	+	
	cł	nr6	5896321	5896380	CAGEpeak _2	25.03	+	
	cł	nr6	223541	223602	CAGEpeak _3	1.23	-	
	cł	nr17	5012035	5012100	CAGEpeak _4	45.3	+	
	cł	nr21	960032	960098	CAGEpeak _5	8.70	-	SDC
								JAC



## Implementation

**Source code:** https://github.com/gdevailly/HeatStarSeq\_gh



Icons:

## Live demonstration





### www.heatstarseq.roslin.ed.ac.uk





## If live demo fails...









.



. . . . .




Tissue (empty to select all):	
adult mammalian kidney b	
brain	*
bone marrow	
brown adipose tissue	
bone marrow macrophage	=
cere <mark>b</mark> ellum	
fi <mark>b</mark> ro <mark>b</mark> last	
cere <mark>b</mark> ral cortex	
em <mark>b</mark> rvonic stem cell	-
	kidney mk3 ce
	adult mammal adult mammal
	adult mammal adult mammal

L

11

kidney GSM929706 ۱e kidney GSM1015153 kidney GSM1020660 kidney GSM1020643 kidney GSM1020651 adult mammalian kidney GSM752624 adult mammalian kidney GSM752623 adult mammalian kidney GSM752625 spleen GSM759610 spleen GSM759607 spleen GSM759612 spleen GSM759611 spleen GSM759608 spleen GSM759609 spleen GSM1020655 spleen GSM1020664 spleen GSM1020647 spleen GSM929720

#### **Correlation coefficient**



#### 3 - Plot customization

I Highlight my experiment in the heatmap.

Tissue (empty to select all):

Developmental stage (empty to select all):

Library type (empty to select all):

Uploaded experiment correlation correction:

•

Ŧ

-

None

Advanced clustering option

abei size.Automatic

O Adjust manually

Show dendrogram(s)?

both

Show labels?

both

Customise colours

Distance calculation:	
euclidean	•
Clustering method:	

#### 3 - Plot customization

I Highlight my experiment in the heatmap.

Tissue (empty to select all):

Developmental stage (empty to select all):

Library type (empty to select all):

Uploaded experiment correlation correction:

Ŧ

-

•

None

Label size:

Automatic

O Adjust manually

Show dendrogram(s)?

both

Show labels?

both

Customise colours
Colour 1:
#FFFFF
Value 1:
-1 -0.83 -0.66 -0.49 -0.32 -0.15 0.02 0.19 0.36 0.53 0
Colour 2:
#FFFFF
Value 2:
0.75 0.76 0.76 0.77 0.78 0.78 0.79 0.8 0
Colour 3:
#FF8800
Value 3:
0.85 0.85 0.86 0.86 0.87 0.88 0.88 0.89 0.89 0.9 0
Colour 4:
#000000
Value 4: 0.95
0.95 0.95 0.96 0.96 0.97 0.97 0.98 0.98 0.99 0.99

Apply colour changes

#### Correlation coefficient







adult mammalian kidney GSM752623 adult mammalian kidney GSM752625 adult mammalian kidney GSM752624 adult mammalian kidney GSM1020651 adult mammalian kidney GSM1020643 adult mammalian kidney GSM1020660 adult mammalian kidney GSM1015153



🖨 Heat*seq	Use application	Instructions					
HeatRNAseq		My express amples me	ion file Correlation table	Static heatmap	Responsive heatmap	Tree	Pairwise plot
Show 25 💌 entries			Search:				
geneName		⇒ value		÷			
ENSMUSG0000000001		4.263310e+01					
ENSMUSG000000003		0.000000e+00					
ENSMUSG0000000028		7.597450e-01					
ENSMUSG0000000031		0.000000e+00					
ENSMUSG0000000037		0.000000e+00					
ENSMUSG0000000049		1.924590e+01					
ENSMUSG0000000056		1.318474e+01					
ENSMUSG0000000058		1.964318e+01					
ENSMUSG0000000078		7.670450e+00					
ENSMUSG000000085		1.740366e+01					
ENSMUSG000000088		3.714490e+02					
ENSMUSG000000093		2.252150e+01					
ENSMUSG0000000094		0.000000e+00					
ENSMUSG0000000103		1.650000e-07					

🖀 Heat*seq	Use application	Instructions						
			My expression file	Correlation table	Static heatmap	Responsive heatmap	Tree	Pairwise plot
HeatRNAseq			Samples metadata					
				+				

Show 25 • entries	Search:
experiment	correlation
adult mammalian kidney GSM1020643	0.9280321
adult mammalian kidney GSM1020651	0.9261101
adult mammalian kidney GSM1020660	0.9163906
adult mammalian kidney GSM752624	0.9133589
adult mammalian kidney GSM752625	0.8998140
adult mammalian kidney GSM752623	0.8988885
adult mammalian kidney GSM1015153	0.8955616
adult mammalian kidney GSM929706	0.8497051
female gonad GSM1196047	0.7943039
lung GSM759602	0.7912177
female gonad GSM1196046	0.7909049
colon GSM1020641	0.7901953



## Mouse hovering widget

Zoom by drag and drop

Send plot to plotly and share with



<mark> H</mark> eat*seq	Use application	Instructions				
leatRNAseq		My expression file Samples metadata	Correlation table Station	c heatmap Respons	sive heatmap Tree	Pairwise plot
		<b>L</b>				
Show 25 🔹 entri	es				Search:	
geoAccession	tissue			libraryType	<b>♦</b> url	\$
GSM752614	brain	brain GSM752614	post-juvenile adult stage	single	link	
GSM752615	brain	brain GSM752615	post-juvenile adult stage	single	link	
GSM752616	brain	brain GSM752616	post-juvenile adult stage	single	link	
GSM752617	cerebellum	cerebellum GSM752617	post-juvenile adult stage	single	link	
GSM752618	cerebellum	cerebellum GSM752618	post-juvenile adult stage	single	link	
GSM752619	cerebellum	cerebellum GSM752619	post-juvenile adult stage	single	link	
GSM752620	heart	heart GSM752620	post-juvenile adult stage	single	link	
GSM752621	heart	heart GSM752621	post-juvenile adult stage	single	link	
GSM752622	heart	heart GSM752622	post-juvenile adult stage	single	link	



Add regression line (blue)

Add guide line (red)



# Conclusions



- A lightweight web application
- Quick comparison of RNA-seq, ChIP-seq and CAGE experiments
- First step to guide you before in depth analysis





# What's next



- Other datasets (suggestions?)
- Other data types (Histones, DNAse1, Gene Lists/Ontologies)
- Multiple user files
- Gene name converter / *liftover* integration









## **Functionnal annotation transfert using co-expression networks** Pía Francesca Loren Reyes, Tom Michoel, Anagha Joshi, Guillaume Devailly







- \* Plenty of *omic* data
- \* Not enough functional annotations :(
- \* Can we use *omic* data to improve functional annotations?





- Functional annotations are often inferred from other species
- This lead to over-annotations mistakes, notably in the cases of one-to-many or many-to-many homology groups
- Hypothesis: if two orthologs are in the same co-expression cluster in different species, then functional annotation are likely to be transferable.

And co-expression cluster are easy to build from public *omic* data! \o/



# Public microarray expression data



Mous		Rat	
Series ID	n	Series ID	n
total	920	total	620
GSE50789	96	GSE13270	101
GSE9630	59	GSE59495	90
GSE55756	47	GSE24104	47
GSE63027	39	GSE5509	40
GSE51885	27	GSE23748	30
GSE38067	24	GSE27625	30

. . .

Affymetrix Mouse Genome 430 2.0 Affymetrix Rat Genome 230 2.0



. . .

Mous		Rat	
Series ID	n	Series ID	n
total	248	total	1202
GSE1479	36	GSE57822	433
GSE3530	36	GSE57800	429
GSE7487	24	GSE19290	82
GSE5500	21	GSE6104	45
GSE7605	18	GSE7999	30
GSE3440	15	GSE11851	20











rat

Species	Category	Term	Gene	$\overline{\mathbf{FE}}$	P-value
Mouse	Reactome	Synthesis of (16-20)-hydroxyeicosatetraenoic	11	4.78	4.29E-02
		acids (HETE)		4 9 4	
		Activation of gene expression by SREBF (SREBP)	15	4.34	5.18E-03
		Regulation of cholesterol biosynthesis by SREBP (SREBF)	17	3.94	4.36E-03
		Cytochrome P450 - arranged by substrate type	27	2.72	7.78E-03
		Phase 1 - Functionalization of compounds	37	2.55	7.58E-04
	GO slim BP	fatty acid metabolic process	52	2.26	2.95 E-05
		steroid metabolic process	50	2.18	1.31E-04
Rat	Reactome	Synthesis of bile acids and bile salts via 24-	7	8.63	2.95E-02
		hydroxycholesterol			
		Endosomal/Vacuolar pathway	10	7.93	1.15E-03
		Striated Muscle Contraction	11	6.78	1.48E-03
		ER-Phagosome pathway	10	6.53	6.29E-03
		Activation of gene expression by SREBF (SREBP)	10	6.53	6.29E-03
		Antigen Presentation: Folding, assembly and peptide loading of class I MHC	13	6.27	3.84E-04
		Regulation of cholesterol biosynthesis by SREBP (SREBF)	10	5.55	2.51E-02
		Biological oxidations	25	2.95	3.58E-03
		Metabolism of lipids and lipoproteins	68	2.13	1.15E-05
	GO slim BP	response to biotic stimulus	12	4.16	1.12E-02
		fatty acid metabolic process	22	2.52	2.52E-02

053 7-12-19















.056 2017-12-19

	Homology group	Species	Gene name	SCHype cluster		_
d)	137229			cluster 69		_
č		mouse	Anp32a	$\checkmark$		
<b>D</b>		$\operatorname{rat}$	Anp32a	$\checkmark$		
ŏ		$\operatorname{rat}$	LOC100909983			
0	68982			cluster 7	cluster 30	
Ē		mouse	Ccnb1	$\checkmark$	$\checkmark$	
0		mouse	Gm5593			
		$\operatorname{rat}$	Ccnb1	$\checkmark$	$\checkmark$	
	10699			cluster 2	cluster 118	
		mouse	Cd248	$\checkmark$	$\checkmark$	
		$\operatorname{rat}$	Cd248	$\checkmark$	$\checkmark$	
		$\operatorname{rat}$	LOC100911932			
		$\operatorname{rat}$	LOC100911882			
	3938			cluster 1		
		mouse	Ppp1r3c	$\checkmark$		
		$\operatorname{rat}$	Ppp1r3c	$\checkmark$		
		$\operatorname{rat}$	LOC100910671			
	14108			cluster 2		
		mouse	Rasl10b	$\checkmark$		
		$\operatorname{rat}$	Rasl10b	$\checkmark$		05
SCIENCE & IMPACT		$\operatorname{rat}$	LOC100912246			7-12-

Homology group	Species	Gene name	SCHype cluster			
128630			cluster 9	cluster 12	cluster 45	
	mouse	Ceacam1	$\checkmark$			
	mouse	Ceacam2	$\checkmark$	$\checkmark$	$\checkmark$	
	rat	Ceacam1	$\checkmark$	$\checkmark$	$\checkmark$	
11456			cluster 5			
	mouse	Elovl 6	$\checkmark$			
	rat	Elovl 6	$\checkmark$			
	rat	LOC102549542	$\checkmark$			
20277			cluster 35			
	mouse	Rrm2	$\checkmark$			
	rat	Rrm2	$\checkmark$			
	rat	LOC100359539	$\checkmark$			
55991			cluster 1	cluster 119		
	mouse	Tmed2	$\checkmark$	$\checkmark$		
	mouse	Gm21540	$\checkmark$	$\checkmark$		
	rat	Tmed2	$\checkmark$	$\checkmark$		
11890			cluster 10	cluster 43	cluster 81	
	mouse	Tnks2	$\checkmark$	$\checkmark$	$\checkmark$	
	rat	<i>LOC100910717</i>	$\checkmark$	$\checkmark$	$\checkmark$	
	$\operatorname{rat}$	Tnks2	$\checkmark$	$\checkmark$	$\checkmark$	

Homo	logy group	$\mathbf{Species}$	Gene name	SCHype cluster
	117948			cluster 102
		mouse	Cyp2c38	$\checkmark$
		mouse	Cyp2c29	
		mouse	Cyp2c39	
		$\operatorname{rat}$	Cyp2c7	$\checkmark$
	104115			cluster 33
		mouse	Hsd3b5	$\checkmark$
		mouse	Gm10681	
		mouse	Hsd3b4	
		mouse	Gm4450	
		rat	Hsd3b5	$\checkmark$
		rat	LOC100911116	$\checkmark$
	137425			cluster 2
		mouse	Lce3c	$\checkmark$
		$\operatorname{rat}$	LOC100361951	$\checkmark$
		$\operatorname{rat}$	LOC100911982	$\checkmark$
		$\operatorname{rat}$	Lce3d	
	129514			cluster 17
		mouse	Rdh9	$\checkmark$
		mouse	Rdh1	
		mouse	Rdh16	
		mouse	Rdh19	
		mouse	BC089597	
G_D		$\operatorname{rat}$	Rdh16	$\checkmark$
		$\operatorname{rat}$	LOC100365958	$\checkmark$

.059

2017-12-19

SCIENCE & IMPACT



# Conclusions &

- \* Plogical Petidence for resolving functional annotation transfer in 28 complex homology groups (>100 genes)
- \* Using free data!
- \* Different array, RNA-seq
- More tissues!
- More species!
- Still need functional annotation in at least one species









## Epigenomics and the human transcript diversity using Roadmap Epigenomics data





ROADMAP

epigenomi



- \* Epigenetic marks role at TSS and enhancer is (quite) well characterized
- Putative roles in TES, exon recognition, cryptic TSS repression?



- Plenty of data generated by Roadmaps Epigenomics (+ENCODE)
- RNA-seq, WGBS, DNAse1, plenty of HisMod in > 30 cell types





## What's a gene?



### Version 27 (January 2017 freeze, GRCh38) - Ensembl 90 General stats

Total No of Genes

58288







**@G** Devailly

SCIENCE & IMPACT





## Which metric for DNA methylation?



mCpG density main driver of methylation









.067 2017-12-19





.068 2017-12-19





.069 2017-12-19





.070 2017-12-19
















 Features × marks × cell types × gene types
Combinatorial explosion: >5000



-2kb

-2kb

-2kb



pseudogenet

RNA gene

Epigenetic marks at

promoters and transcription level in H1 embryonic

stem cells

























G\_Devailly



# Epigenetic marks at intron/exon boundaries?



SCIENCE & IMPACT @G\_Devailly



# Epigenetic marks at intron/exon boundaries?



SCIENCE & IMPACT



- \* Epigenetic marks and **alternative** splicing?
- \* Gene by gene tool in webapp
- \* Polish, write and submit













Anagha Jos Anina Mantsok Barry Horne Tom Michoel





Angeles Arzalluz-LuqueDeepti Vipin Pia Francesca Loren Reyes



Illustrations: smart.servier.com, BY







### Epigenetics and heritability

- missing heritability
- Improving livestock epigenome

Non-heritable epigenetics

\* Early prediction?



#### Variant annotation

# (physiology and nutrition)



