

# **ISMARA & CREMA tutorials**

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Swiss Institute of<br>Bioinformatics

# **Agenda**

- 9:00 10:30 **ISMARA**: Introduction to Motif Activity Response Analysis (MARA) modeling gene expression in terms of regulatory sites. Theory and overview of the results.
- $\cdot$  10:30 11:00 Coffee break
- 11:00 12:30 **CREMA**: Cis-regulatory Element Motif Activities. Modeling chromatin state genome-wide in terms of regulatory sites. Theory and overview of the results.
- $\cdot$  12:30 13:30 Lunch break
- 13:30 15:00 **Using the web interface**: Supported species, data types and formats, uploading data, downloading result, and advanced interactive features.
- $\cdot$  15:00 15:30 Coffee break
- 15:30 17:00 Hands-on exercises. Users explore results using their own datasets.





Web-based tools & services

- **A** Software
- 区 Genome annotations
- Documentation & Help
- **L** Contact us



Resources for regulatory genomics

Web-based tools & services

# swissregulon.unibas.ch

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ISMARA: The Integrated System for Motif Actitivity Response Analysis.

Swiss Regulon

Input DATA: RNA-Seq, ChIP-Seq, microarray. Analysis: Infers key regulators (TFs/microRNAs) and gene regulatory interactions from expression data.



**CREMA:** Cis-Regulatory Element Motif Activities.

Input DATA: ATAC-Seq, DNase-Seq, ChIP-Seq. Analysis: Infers CREs genome-wide and the key TFs that regulate their chromatin state (i.e. accessibility or epigenetic marks) across a set of samples.



CRUNCH: A completely automated pipe-line for TF ChIP-Seq analysis.

Input DATA: TF ChIP-Seq. Analysis: Peak identification and comprehensive annotation of regulatory motifs and sites in peaks.



REALPHY: Reference sequence Alignment based Phylogeny.

Input DATA: Genome assemblies or raw genomic sequencing reads.

Analysis: Core genome alignment and phylogenetic tree.



RECOPHY: A recombination pattern analysis in related prokaryotic species.

Input DATA: Genome assemblies or raw genomic sequencing reads.

Analysis: A range of summary statistics, such as the fraction of SNPs supporting each branch of a tree and the fraction of clonal and recombined genome between each pair of strains.



Phylogibbs: A Gibbs sampling motif finder for multiple alignments.

Input DATA: Multiple alignments of DNA sequences. Analysis: De novo identification of regulatory motifs with rigorous incorporation of conservation information.

### **ISMARA**

### Automatically inferring key gene regulatory circuitry from gene expression data





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How is the regulatory code in the DNA `read out' to control cell fate and identity?





**white and red blood cells egg cell with 2 coronal cells three neurons**





### **osteoclasts How do gene regulatory networks function as** *systems***.**

- What is a cell type?
- How is cell identity stabilized?
- Where is the key information? What does not matter?











How is the regulatory code in the DNA `read out' to control cell fate and identity?





**white and red blood cells egg cell with 2 coronal cells three neurons**





### **how do gene regulatory networks function as** *systems***. The extending osteoclasts of the** *systems***.**

- What is a cell type?
- How is cell identity stabilized?
- Where is the key information? What does not matter?

#### **My worries**

- We think we know/measure a lot, but there is orders of magnitude more we do not know.
- Nowhere near the ability to meaningfully model what is going on.
- High-throughput measurements full of artifacts and biases that we poorly understand.
- Data analysis typically involves dizzying arrays of normalizations, filters, and transformations.

### **What useful things can computational analysis offer?**

Robust and transparent methods that help guide experimental efforts.



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## What does my transcriptome/epigenome data say about regulation in my system?

#### **Typical questions:**

What are the key regulators? What are their roles? Which pathways do they target?



#### **Challenges**

- Cannot do saturating genetic screens (too many candidate TF/miRNA regulators).
- Easy to do high-throughput measurements (microarray, RNA-seq, ChIP-seq, ATAC-seq).
- *Experimental labs often do not have the expertise to infer regulation from such data.*
- Collaborations with dedicated computational labs on a *per case* basis are big investment of time and effort.



### Typical analysis of transcriptomic data

### **Basic processing**

- Map raw reads to transcripts.
- Find all genes that are expressed.

#### METHOD OPEN ACCESS

Differential expression analysis for sequence count data

Simon Anders and Wolfgang Huber

Genome Biology 2010 11:R106 https://doi.org/10.1186/gb-2010-11-10-r106 © Anders et al 2010 Received: 20 April 2010 Accepted: 27 October 2010 Published: 27 October 2010

• Find genes that are *differently expressed* across conditions, e.g. using *DESeq*.



#### Ketone metabolism Lipid droplet and  $(1.6\%)$ **VLDL** metabolism  $(13%)$ Lipid Carbohydrate metabolism Metabolism  $(43%)$  $(23%)$ **Cholesterol and** bile acid metabolism  $(19%)$

### **Limitations of these traditional approaches**

- Does not infer anything about gene *regulation*.
- Often unclear how to experimentally follow-up.



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### **Clustering genes with similar expression Enriched categories among gene sets**

### Completely automated prediction of regulatory interactions from high-throughput data



#### **Upload raw micro-array oe RNA-seq data and predict:**

- Key regulators (TFs/miRNAs) in the system.
- Regulator activities across the input samples.
- Sets of target genes and pathways for each regulator.
- The regulatory sites on the genome through which each regulator acts.
- Interactions between the regulators.

### Modelling gene expression and chromatin state in terms of TFBS using a linear model





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### Modelling gene expression and chromatin state in terms of TFBS using a linear model





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### Constructing reference promoteromes and transcriptomes

#### **Input data**

- Collections of experimentally measured transcription start sites (e.g. CAGE).
- Collections of know full-length mRNAs (e.g. Genbank, Gencode, or Ensembl).

#### Methods for analyzing deep sequencing expression data: constructing the human and mouse promoterome with deepCAGE data

Piotr J Balwierz, Piero Carninci, Carsten O Daub, Jun Kawai, Yoshihide Hayashizaki, Werner Van Belle, Christian Beisel and Erik van Nimwegen

Genome Biology 2009 10:R79 https://doi.org/10.1186/gb-2009-10-7-r79 © Balwierz et al.; licensee BioMed Central Ltd. 2009 Received: 23 October 2008 Accepted: 22 July 2009 Published: 22 July 2009



#### **Procedure: Cluster nearby TSSs with mRNA starts**

- mRNA starts are clustered with TSSs within 150bps (one nucleosome) of each other.
- Each cluster corresponds to a promoter.
- Only clusters with associated transcripts are retained.



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# Regulatory motifs represent sequence binding preferences of transcription factors

**Position specific weight matrix representation (sequence logos):** 



#### **Example**: E. coli's **fruR** binding sites and weight matrix

AAGCTGAATCGATTTTATGATTTGGT AGGCTGAATCGTTTCAATTCAGCAAG CTGCTGAATTGATTCAGGTCAGGCCA GTGCTGAAACCATTCAAGAGTCAATT GTGGTGAATCGATACTTTACCGGTTG CGACTGAAACGCTTCAGCTAGGATAA TGACGAAACGTTTTTGCCCTATGAG TTCTTGAAACGTTTCAGCGCGATCTT ACGGTGAATCGTTCAAGCAAATATAT GCACTGAATCGGTTAACTGTCCAGTC ATCGTTAAGCGATTCAGCACCTTACC \*\*gcTGAAtCG\*TTcAg\*\*c\*\*\*\*\*\*

bits



*w* α  $\alpha$ <sup>*i*</sup> = Probability of finding base  $\alpha$  at position *i*. Example, position 4:  $w_A^4 = 0.06$ ,  $w_C^4 = 0.53$ ,  $w_G^4 = 0.27$ ,  $w_T^4 = 0.13$ 

 $P(s \mid w) = \prod w$ 

*l*

*i si*

*i*

1

Probability that a site for the TF has sequence *s*:<br> **BIOZENTRUM** 



### Predicting transcription factor binding sites using comparative genomics**: MotEvo**

#### **TF binding site prediction procedure**

- For each promoter, collect promoter sequence plus 500bp upstream and 500bp downstream.
- Align each promoter region with orthologous regions from other species.
- For each motif in the motif collection, predict binding sites using the MotEvo algorithm.



## Genome-wide annotation of regulatory sites in promoters

**Example**: Predicted TFBSs in the proximal promoter of the SNAI3 TF.



#### **Summarizing the TFBS predictions**

Sum the posteriors of the predicted sites for each motif to obtain a **matrix of site-counts**:

$$
N_{pm}
$$
 = Total number of sites for motif *m* in promoter *p*.



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# Including regulation by miRNAs

#### **miRNAs destabilize mRNAs by hybridizing to sites in their 3' UTRs.**



**Sites with a perfect seed match show strong conservation**

We include predicted sites for 86 seed families (based on seed conservation analysis from TargetScan version 7). **Site counts**:

 $N_{p\mu}$  = Average number of sites for seed motif  $\mu$  in transcripts associated with promoter *p*.



# Curating a set of mammalian motifs and sites

- 1. Large motif collection from: SwissRegulon, CRUNCH, JASPAR, Hocomoco, Homer, Uniprobe, Encode, HT-SELEX.
- 2. Multiple candidate motifs for each transcription factor (TF).
- 3. Selecting an optimal set of motifs: Run ISMARA on the **FANTOM5 expression atlas** (889 human/388 mouse samples) selecting one motif per TF (simulated annealing).
- **4. Redundancy removal**: Collapse similar motifs with statistically indistinguishable activities in the FANTOM5 atlas (Bayesian model selection).





**Daniel Schmocker**





Nature, 2014 Mar 27;507(7493):462-70. doi: 10.1038/nature13182. A promoter-level mammalian expression atlas. FANTOM Consortium and the RIKEN PMI and CLST (DGT).

#### **Reverse cumulative: explained variance per sample**



fraction of explained variance



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### Modeling gene expression and chromatin state in terms of TFBS using a linear model





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# Quantifying genome-wide expression



# Mapping reads to transcripts

- Each RNA-seq read is mapped to the *transcriptome* using Kallisto.
- The weight of each read is distributed *uniformly*  over all transcripts consistent with it.



Affiliations | Contributions | Corresponding author

Nature Biotechnology 34, 525-527 (2016) | doi:10.1038/nbt.3519 Received 15 October 2015 | Accepted 25 February 2016 | Published online 04 April 2016



- Each transcript's total weight  $w_t$  is the sum of the weights of all reads mapping to the transcript. Then weight is divided by transcript length  $W_t = w_t/L_t$ .
- A promoter's total weight  $W_p$  is the sum of the weights of its transcripts:  $W_p = \sum_{t \in p} W_t$
- A pseudo-count is added (constant corresponding to 0.5 tpm):  $W_{n} \to W_{n} + \lambda$ *p p*
- The weights are rescaled to represent transcripts-per-million (tpm), and log-transformed:

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$$
E_p = \log_2 \left[ 10^6 \frac{W_p}{\sum_{\tilde{p}} W_{\tilde{p}}} \right]
$$



### Modeling gene expression and chromatin state in terms of TFBS using a linear model





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### **MARA's linear model**

- Measurements are represented as a matrix  $E_{_{ps}}$  of expression across all promoters and samples.
- Each sample (column of the matrix) is normalized by subtracting the mean expression, and site counts are normalized to sum to zero across promoters.

$$
E_s = \frac{1}{P} \sum_p E_{ps} \qquad E_{ps} \rightarrow E'_{ps} = E_{ps} - E_s \qquad N_m = \frac{1}{P} \sum_p N_{pm} \qquad N_{pm} \rightarrow \tilde{N}_{pm} = N_{pm} - N_m
$$

• We model the expression in terms of the site counts and *motif activities*

$$
E'_{ps} = noise + \sum_{m} \tilde{N}_{pm} A_{ms}
$$

• We separate the fitting into a fit of the **average expression***:*

$$
\langle E'_{p} \rangle = \frac{1}{S} \sum_{s} E'_{ps} \langle A_{m} \rangle = \frac{1}{S} \sum_{s} A_{ms}
$$
 model:  $\langle E'_{p} \rangle = noise + \sum_{m} \tilde{N}_{pm} \langle A_{m} \rangle$ 

• And fitting of **expression changes** across the conditions:

*E*! *ps* = *E*' *ps*− *E*' *p A*! *ms* = *A ms* − *A m E*! *ps* = *noise* + *N pm A*! *ms m* ∑ **Note:** *E*! *ps s* ∑ <sup>=</sup> *<sup>A</sup>*! *ms s* ∑ <sup>=</sup> <sup>0</sup>



### **Fitting MARA's linear model (technical)**

$$
\tilde{E}_{ps} = noise + \sum_{m} \tilde{N}_{pm} \tilde{A}_{ms}
$$
 Assume the noise is Gaussian gives likelihood:  
\n
$$
P(\tilde{E} | \tilde{A}) \propto \exp \left[ -\frac{\sum_{p,s} (\tilde{E}_{ps} - \sum_{m} \tilde{N}_{pm} \tilde{A}_{ms})^2}{2\sigma^2} \right]
$$
 To avoid overfitting, we include  $\tilde{A}^*$  and the

fitting, we include a or (with average zero) over es (ridge regression):

 $P(\tilde{A} | \lambda) \propto \exp \left(-\frac{\lambda^2}{2}\right)$  $\frac{\lambda}{2\sigma^2}\sum_{m,s}\tilde{A}_s$ *ms* 2 *m*,*s*  $\left[-\frac{\lambda^2}{2\sigma^2}\sum\right]$  $\lfloor$  $\left|-\frac{\lambda^2}{2\sigma^2}\sum \tilde{A}_{ms}^2\right|$  $\Box$  $\vert$ The optimal posterior activities  $A_{\mu\nu}^{\dagger}$  and the posterior distribution over the activities can be easily determined through Singular Value Decomposition:  $\tilde{\tilde{A}}_{\rm ms}^*$ \*

$$
P(\tilde{A}_{s} | \tilde{E}_{s}, \lambda) \propto \exp\left[-\frac{P}{2\chi_{s}^{2}}\sum_{m,\tilde{m}}(A_{ms} - A_{ms}^{*})W_{m\tilde{m}}(A_{\tilde{m}s} - A_{\tilde{m}s}^{*})\right]
$$
 Here we have defined:  

$$
W_{m\tilde{m}} = \sum_{p} \tilde{N}_{pm} \tilde{N}_{p\tilde{m}} \tilde{N}_{p\tilde{m}} + \lambda^{2} \delta_{m\tilde{m}} \qquad A_{ms}^{*} = \sum_{m,p} W_{m\tilde{m}}^{-1} \tilde{N}_{p\tilde{m}} \tilde{E}_{ps} \qquad \chi_{s}^{2} = \sum_{p} \left(\tilde{E}_{ps} - \sum_{m} \tilde{N}_{pm} A_{ms}^{*}\right)^{2}
$$

The parameter  $\lambda$  of the prior is optimized by maximizing the likelihood of the data, marginalizing over all motif activities.



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### **Bayesian inference of the motif activities**

Obtain both best-fit activities and error-bars on the activities:

$$
A_{ms}^* =
$$
 Fitted activity of motif *m* in sample *s*.

$$
\delta A_{\rm ms} =
$$
 Error-bar on the activity.

**Significance of motif** *m***:**

$$
z_m = \sqrt{\frac{1}{S} \sum_{s=1}^{S} \left(\frac{A_{ms}^*}{\delta A_{ms}}\right)^2}
$$

#### **Notes**

- Motif activities capture the expression *changes* across the input samples.
- Activity meaning:  $\overline{A}_{ms}^*$  is the amount by which log-expression of a transcript is predicted to go up in sample *s* when a site for motif *m* is added to its promoter. \*
- Significance meaning:  $z_m$  is the typical number of standard-deviations that the activity of motif *m* is away from its average of zero.

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### **Example dataset:** Mouse liver development

### Ontogeny of Hepatic Energy Metabolism Genes in Mice as Revealed by RNA-Sequencing

Helen J. Renaud, Yue Julia Cui, Hong Lu, Xiao-bo Zhong, Curtis D. Klaassen

Published: August 7, 2014 • https://doi.org/10.1371/journal.pone.0104560

RNA-seq at 12 time points (in triplicate). Starting 2 days before birth, until 60 days after birth.

#### GD 17.5 prebirth Day 0 Day 1 Day 3 Day 5 suckling Day 10 Day 15 Day 20 **Day 25** Day 30 weaning ∥г Day 45  $Day 60$ High

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#### **Clustering of expression profiles Time-dependent expression of genes in different metabolic categories**



### **Example dataset:** Mouse liver development

- **1.** Go to: ismara.unibas.ch.
- **2**. Click on the 'Example results' tab.
- **3**. The mouse liver datasets are at the top.





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### Most significant motifs (all samples)



#### • Top motifs sorted by significance.

- Z-values.
- Names of the associated TF genes.
- Thumbnails of the motif activity across the time course.
- Sequence logos of the binding patterns of these motifs.



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### **Example dataset:** Mouse liver development

- **1.** Go to: ismara.unibas.ch.
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### Most significant motifs (replicate averaged)



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### Most significant motifs (replicate averaged)



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### Information regarding the HNF4a motif



#### **Notes**

- Motif activity increases with time.
- This means the *targets* of HNF4a (on average) increase expression with time.
- From -0.4 to 0.3 means the average effect of a single HNF4a site goes from 40% reduction of expression to 30% increase in expression relative to average expression.

### Information regarding the HNF4a motif





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### Example with two TFs for one motif: E2F2\_E2F5



### **Interpretation**: both TFs bind to the same binding sites.



E2f2 is both higher expressed and correlates much better with the motif activity.



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### Example of a negatively correlated motif: Cebpe



**Interpretation**: Cebpe is acting as a *repressor* in this system.



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 $0.15$ 

### Predicting targets of each motif (conceptual)

- For each motif, select promoters with predicted sites, i.e with  $N_{_{\scriptsize{pm}}}>0$
- *Mutate* promoter *p* to *remove* the binding site(s) for motif *m*:  $N_{pm} \rightarrow 0$ <br>• Updated site-count matrix:  $N \rightarrow \tilde{N}$
- Updated site-count matrix:  $N \rightarrow \tilde{N}$
- Log-likelihood ratio of fitting all data with  $N$  versus the mutated  $\tilde{N}$ :

$$
S_{pm} = \log \left[ \frac{\int dA P(E \mid N, A)}{\int dA P(E \mid \tilde{N}, A)} \right]
$$

Quantifies the contribution of motif *m* to explaining the expression pattern of promoter *p*.



The log-likelihood ratio *Spm* quantifies how much the quality of the fit is reduced when the sites for motif *m* in promoter *p* are removed.



### Predicting targets of each motif (technical)

 $S_{pm} = \log \left| \frac{\int dA P(E \mid N, A)}{\int dA P(E \mid \tilde{N} A)} \right|$  $\int dA P(E | \tilde{N}, A)$  $\lceil$ #  $\overline{\phantom{a}}$  $\overline{\phantom{a}}$  $\mathcal{I}$  $\overline{\phantom{a}}$ ' '

The target score is the log-likelihood ratio of the fit of the model when the binding sites for motif *m* are removed from promoter p, i.e. when  $N \rightarrow \tilde{N}$ .

Chi-squared gives square deviation observed and predicted expression:  $\chi_{ps}^2 = \left(E_{ps}^{'} - \sum_m N_{pm}^{'} A_{ms}^{'}\right)^2$ When sites for *m* in promoter *p* are removed, chi-squared becomes:  $\chi^2_{psm} = \left(E_{ps}^{'} - \sum \tilde{N}_{pm}^{'} A_{m's}^{'}\right)^2$ 

To a good approximation, the target score log-likelihood ratio is given by  $S_{pm} = \frac{\sum_s \chi_{psm}^2 - \chi_{ps}^2}{\langle \sqrt{2} \rangle}$ 

where  $\langle \chi^2 \rangle = \frac{1}{PS} \sum_{n=1}^{\infty} \chi_{ps}^2$  is the average chi-squared across all promoters and samples.

- **Interpretation:**
- The target-score measures how much the squared-deviation between fit and model increases when the sites for motif *m* in promoter *p* are removed, relative to the average squared-deviation across all promoters and samples.
- **Notes**:
- Generally, the more samples, the higher the target scores are.
- Target scores can be negative as well (when the predictions are better without the site).

### List of target promoter/genes of HNF4a

Top of the list of HNF4a target promoters, sorted by their significance:

Top targets: Search: Show  $25$  $\div$  entries **Promoter** Score  $\downarrow$   $\bar{z}$ **Transcript** Gene ΠŤ. **Gene Info** Jî IT. chr19\_+\_39287074 ENSMUST00000003137.8 cytochrome P450, family 2, subfamily c, polypeptide 29 95.78  $Cyp2c29$ chr17 - 46438471 solute carrier family 22 (organic anion transporter), member 7 84.62 ENSMUST00000087012.5 SIc22a7 chr4 - 62087261 81.03 ENSMUST00000107488.3 Mup3 major urinary protein 3 ENSMUST00000107472.1 ENSMUST00000084531.4 chr19\_+\_39007019 61.77 ENSMUST00000025966.4  $Cyp2c55$ cytochrome P450, family 2, subfamily c, polypeptide 55 chr4\_-\_60501903 60.52 ENSMUST00000084548.4 major urinary protein 1 Mup1 ENSMUST00000103012.3 ENSMUST00000107499.3 chr19 - 8405060 58.81 ENSMUST00000064507.5 **SIc22a30** solute carrier family 22, member 30 ENSMUST00000120540.1 ENSMUST00000096269.4 58.08 chr19 - 40073731 ENSMUST00000048959.3 Cyp2c54 cytochrome P450, family 2, subfamily c, polypeptide 54 chr4\_-\_62054112 57.75 ENSMUST00000074018.3 Mup20 major urinary protein 20 56.33 ENSMUST00000065651.4 solute carrier family 22, member 28 chr19\_-\_8131982 **SIc22a28** 55.97 chr4 - 60741275 ENSMUST00000117932.1 Mup12 major urinary protein 12 chr19 - 39463067 55.17 ENSMUST00000035488.2 Cyp2c38 cytochrome P450, family 2, subfamily c, polypeptide 38 chr15\_-\_82764176 55.09 ENSMUST00000055721.4 Cyp2d40 cytochrome P450, family 2, subfamily d, polypeptide 40 ENSMUST00000026398.3 Mettl7b methyltransferase like 7B chr10 - 128960965 54.11

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### SwissRegulon view of the Cyp2c29 promoter



Location of the Hnf4A binding site.

This predicts which bases in the promoter are crucial for the regulation by HNF4a.



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### What pathways does HNF4a target? Enriched Gene Ontology categories

Gene overrepresentation in biological\_process category:



- For each Gene Ontology category (starting from the most specific), calculate the sum and average of target log-likelihood scores for the genes in the category.
- Sort all categories by average target score or summed log-likelihood of all genes.
- For each category, remove all genes in this category from other categories lower in the list.
- The table can be searched, expanded, and sorted in different ways.



### What pathways does HNF4a target? STRING-db picture of the network of HNF4a targets



### Direct interactions between HNF4a and other regulators

The constitutive androstane receptor (CAR) also known as nuclear receptor subfamily 1, group I, member 3 is a protein that in humans is encoded by the NR1I3 gene.<sup>[5]</sup> CAR is a member of the nuclear receptor superfamily and along with pregnane X receptor (PXR) functions as a sensor of endobiotic and xenobiotic substances. In response, expression of proteins responsible for the metabolism and excretion of these substances is upregulated.<sup>[6]</sup> Hence, CAR and PXR play a major role in the detoxification of foreign substances such as drugs.



Use slider or -/+ buttons to hide/show edges.



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### Direct interactions between HNF4a and other regulators

The liver receptor homolog-1 (LRH-1) also known as NR5A2 (nuclear receptor subfamily 5, group A, member 2) is a protein that in humans is encoded by the NR5A2 gene.<sup>[5][6]</sup> LRH-1 is a member of the nuclear receptor family of intracellular transcription factors.

LRH-1 plays a critical role in the regulation of development, cholesterol transport, bile acid homeostasis and steroidogenesis. [7][8][9]

LRH-1 is important for maintaining pluripotence of stem cells during embryonic development. [10]



Score threshold: 4.675 Use slider or -/+ buttons to hide/show edges.





### Direct interactions between HNF4a and other regulators



Score threshold: 4.675 Use slider or -/+ buttons to hide/show edges.

#### **BIOZENTRUM**

Universität Basel The Center for Molecular Life Sciences J Cell Sci. 1998 Aug; 111 ( Pt 16): 2411-21.

#### Phenotypic effects of the forced expression of HNF4 and HNF1alpha are conditioned by properties of the recipient cell.

Bailly A<sup>1</sup>, Späth G. Bender V, Weiss MC.

### Most significant motifs







### E2f2 and E2f1 targets are down-regulated over time



Note that the motif activities and expression of both factors are very similar. Both are down-regulated across the time course. This suggests we are looking at a single `pathway'.



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### Network of E2f2 target genes

The extremely high density of links shows E2f2 is targeting a very well-studied pathway.

Inspection shows that these are all cell cycle genes, and in particular genes involved in initiation of replication.



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### Pathways most targeted by E2f1 and E2f2 G1 – S transition of the cell cycle

This picture is confirmed when one looks at the top Gene Ontology categories and pathways among the E2f2/E2f1 targets:

#### **Gene overrepresentation in biological\_process category:**



#### **Gene overrepresentation in cellular\_component category:**



#### **Gene overrepresentation in curated gene sets: REACTOME pathways category:**



E2f1/E2f2 are regulating initiation of DNA replication, i.e. transition from G1 to S. The fact that their activity decreases with time likely indicates that the amount of cell division is steadily decreasing during liver maturation.





### **How is a given gene of interest regulated?**





#### **BIOZENTRUM**

### Sortable table of genes with expression statistics



#### **BIOZENTRUM**



### Observed and predicted expression of H2afx



Fraction of explained variance: 0.907

SwissRegulon link: mm10\_v2\_chr9\_+\_44334685\_44334715 Associated genes:

• H2afx: H2A histone family, member X Links -Associated transcripts: ENSMUST00000052686.2

On this plot you can see a contribution of individual motifs into the predicted expression. Use checkboxes in the table on the right side to show or remove impact of a motif to the predicted expression. By default all motifs are turned off.





This plot shows expression and predicted expression of mm10\_v2\_chr9\_+\_44334685\_44334715 promoter. Left vertical axis is a promoter expression on the log2 scale. Right vertical axis is a predicted promoter expression on the log2 scale. Horisontal axis indicates samples.

#### All motifs turned off.



All On All Off



#### **BIOZENTRUM**

### Observed and predicted expression of H2afx

#### Promoter: mm10 v2 chr9 + 44334685 44334715

Fraction of explained variance: 0.907

SwissRegulon link: mm10\_v2\_chr9\_+\_44334685\_44334715 Associated genes:

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#### All motifs turned on.



All Off

All On



#### **BIOZENTRUM**

### Observed and predicted expression of H2afx



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### **Downloadable results for downstream analysis**



avrg: GSE58827: Dynamics of the Mouse Liver

**Navigation** 

Motif significance table

Sample table

**Mean activities** 

by FOV

### **ISMARA results avrg: GSE58827: Dynamics of the Mouse Liver**

ISMARA - Integrated System for Motif Actitivity Response Analysis is a free online tool that recognizes most important transcription factors that are changing their activity in a set of samples.

#### **Original results**

#### Show averaging configuration



These downloadable result files will be discussed in the afternoon session.



#### **BIOZENTRUM**

report

### **ISMARA Acknowledgments** People that helped develop the MARA tool



**Piotr Balwierz** ISMARA development



**Mikhail Pachkov** Web interface and support



**Phil Arnold** MotEvo and epi-MARA



**Jeremie Breda** single-cell MARA



**Ðorđe Relic** zebrafish ISMARA



