Journées NetBIO - 14/10/2019

#### Dynamics of Genes Regulatory Network Governing *de novo* Lateral Root Primordium Development in *Arabidopsis thaliana*

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#### Context : Root System

#### Development

### Root Arcl itecture

Nutrition

Anchorage

Interaction with microorganisms

#### Context : Secondary organogenesis



... to a mature

root system ...

... with a complex architecture resulting from interactions between genetics and environment.

In Arabidopsis, LR initiation occurs in the pericycle

And LR develop through the tissues to finally emerge







#### (Lucas et al. 2013)

#### Context : Lateral root organogenesis

#### Let's have a look at lots of LRP





(Lucas et al. 2013)

#### Let's have a look at lots of LRP





#### Let's have a look at lots of LRP



LRP patterning is not stereotypical

# Multiple ways of building a LRP



Sequence of division events actually varies between LRP



(Lucas et al. 2013)





#### Modulation of lateral root initiation

## LRP initiation correlated with root bending

#### Gravitropism induces root bending



(De Smet et al. 2007)

Can new lateral roots be induced using gravistimulation ?



(Rosen, 1999)

#### Modulation of lateral root initiation



(Lucas et al. 2008)

### Induction of rhizogenesis by gravistimulation

### Gravistimulation induces initiation...

## ... within a tightly controlled spatio-temporal window



(Lucas et al. 2008)

### Control of rhizogenesis by gravistimulation

## Gravistimulation induces initiation...

## ... within a tightly controlled spatio-temporal window



Can we use this to access the dynamics of LR morphogenesis regulation ?



<sup>(</sup>Péret et al. 2012)





300 to 400 bends per timepoint

18 timepoints : 3 hours apart, from before initiation to after emergence

4 replicates

Database of ~8500 differentially expressed genes (inc. 700 TFs)

(Voss et al 2015)

Illustration of some transcription factors expression profiles from the database

12.00

10.00

8.00

6.00

4.00

2.00

0.00

0 6

Log2 expression



Time after gravistimulation

KAN4 TSO1

#### Expression database exploitation

Extracting information from the LR dataset ?

### ↓

Use statistical network inference methods

Developed a new algorithm in our lab (J. Lavenus thesis)

#### A typical time profile for mRNA level in lateral root primordia following gravistimulation



#### Time Delay Correlation - TDCor

• Implemented in R (CRAN)

• Runs on expression profiles extracted from the LR dataset (or any other transcriptomic kinetics dataset)

• Looks for non-combinatorial linear interactions

• Uses Pearson's correlation with time delay computation to produce a preliminary network

• Uses bootstrap and statistical filters to eliminate false positive and refine the network topology



#### TDCor - data treatment pipeline



Lavenus et al., Plant Cell 2015

#### Using TDCor on the LR dataset

Selection of genes involved in

- lateral root formation
- root meristem organization and activity
- hormonal transduction
- cell division
- cell differenciation

Possibility to include any other gene present on the Affymetrix chip (*e.g.* selected because of interesting features of its expression profile ...)



#### Using TDCor on the LR dataset

- Selected a list of 261 genes
- Not only transcription factors
- A "prior" data is given to each gene, based on the litterature, to indicate if transcriptional regulation activity has been reported or not
- This "prior" information helps the inference procedure by authorizing or not the algorithm to draw outward edges from the node. However indicating a prior is not compulsory (prior = 2)

Gene	Name	Prior
AT1G02850	BGLU11	0
AT1G03430	AHP5	0
AT1G03840	MGP	2
AT1G04220	KCS2	0
AT1G04240	SHY2	-1
AT1G04550	BDL	-1
AT1G04610	YUC3	0
AT1G04880	AT1G04880	2
AT1G10470	ARR4	-1
AT1G12820	AFB3	0
AT1G15580	IAA5	-1
AT1G15670	KMD2	-1
AT1G16060	WRI3	2
AT1G17950	MYB52	2
AT1G19050	ARR7	-1
AT1G19180	JAZ1	2
AT1G19220	ARF19	2
AT1G19850	MP	1
AT1G20700	WOX14	2
AT1G23080	PIN7	0
AT1G25410	IPT6	0
AT1G25470	CRF12	1
AT1G26680	B3	2
AT1G26870	FEZ	2
AT1G27320	AHK3	0
AT1G27450	APT1	0
AT1G28130	GH3.17	0
AT1G30330	ARF6	1
AT1G30490	PHV	2
AT1 021 220		2

#### Using TDCor on the LR dataset

ARF8	CRF8	АРТВ	AXR4	GH3.5	CYCB1.1	ABIL4	GATA23	СРС	ARF4	МР	CLV1	AHP1	ARR4	WRKY43
LOG6	ANT	PGP4	FEZ	PIN	PLT7	PHV	ARR15	CDKB2.1	MYB41	BRI1	RGF8	CRF1	АРТ4	PT5
ARF16	AGL21	ARR6	CRF12	CNA	PES	HAT2	AtMYB93	CYCAZ.4	ROW1	AGL14	B3	HDG1	ARR11	ADK1b
YUCE	SLR	ARR14	BOP2	BGLUI1	GH316	EXPA17	CLF	ARR16	YUC2	APT2	IAA11	ARR10	ATML1	
PLT5	WRI3	PIN7	ARF17	СКХЗ	AHK5	ACS11	WER	CLV1.like2	EXPA4	АНК2	Скхб	BIG ASA1	MAIL1	LBD17
	ARF19	IAA29		BBM	LBD4	MEL4	LOG2	ACR4	НАМЗ	WOX13	GH3.17	AT3G11280	APT1	SHR
PIN	SHP1	EXPA20	ADK2	CYCD2.1	CYCD6.1	CKX4	AHP6	AFB1	AFB2	ARR17	MELT	EGL3	HAM1	IAA2
JKD	IPTZ	LBD18	ARR3	AHP3	ZF3	LBD33	NAP	AHKS	C2FC	GL2	PUB4	HAM2	Анр2	AUX1
СОІІ	ABI8	AFBB	KMD2	KCSZ	ARR12	GH3,3	U-box	РНВ	WOE.AHK4	AHK1	PID2	KMD1	тмот	WOX14
MAIN	ARR7	CLV1.like3	IPT	KAN4	MAB4	PLT3	IAA19	CYCD1.1	JAZ1	ARF7	Πι	IPHPT1	JUC8	LOG5
Stimulus	ADK	TAR2	MEL2	ARF1	CYCD3.1	MYB52	HAT22	ARR2	ARF18	ARR9	IPT6	RBR1	тмо5	LOG3
МҮВ56	BDL	LAX3	IAA18	тмоб	CRF2	PIN3	CUC3	KAN1	KRP2	PLT2	TAA1	IAA5	CLV1.like4	LOG7
EZFA	EXPA14	CYP735A2	BAK1	CLE2	PID	IAA1	WAG1	LOG4	YUC3	ARF6	CK.N.GT	CRF6	PI	IAA28
LOGS	CRF11	RGF7	REV	AT5G06270	CRF3	APT5	ARR8	DPA	снз 1	ARR23	CYP735A1	HDG12	ARF9	LOG9
AT1G04880	MYB53	IPT3	CLV2	SCR	WAD2	IAA1B	ARF2	ETO1	TIR1	PLT1	СК	CRF5	ADK1	AtWIP4
LBD29	U.box	LRP1	SHY2	🗧 рисні	ARR5	CLV1.like1	LBD16	IPT9	PIN1	WKRY56	PCP19	CRF10	CKX1	GCN5
YUCS	SMB	MGP	PKL	bZIP8	LHW	RGF4								
													Cyt	toscap

Generated a full network (~3h computation on standard PC) With indices of confidence and directness for each interaction. But are we confident in the predictions ?



ARF7 is predicted to occupy a upstream position in the network

ARF7 is predicted to positively regulate a LOB/PUCHI genetic module





NAA DEX CHX NAA+DEX NAA+CHX DEX+CHX NAA+DEX+CHX





#### Moving forward with the network

ARF8	CRF8	АРТА	AXR4	CH3.5	CYCB1.1	ABIL4	GATA23	СРС	ARF4	МР	CLV1	AHP1	ARR4	WRKY43
LOC6	ANT	PGP4	FEZ	PIN	PLT7	PHV	ARR15	CDKB2.1	MYB41	BRI1	RGF8	CRF1	APT4	PT5
ARF16	AGL21	ARR6	CRF12	CNA	PES	HAT2	AtMYB93	CYCA2.4	ROW1	AGL14	B3	HDG1	ARR11	ADK1b
YUC5	SLR	ARR14	BOP2	BGLUI1	GH3:6	EXPA17	CLF	ARR16	YUC2	APT2	IAA11	ARR10	ATML1	
PLT5	WRI3	PIN7	ARF17	СКХЗ	АНК5	ACS11	WER	CLV1,like2	EXPA4	АНК2	CKX6	BIG.ASA1	MAIL1	LBD17
	ARF19	IAA29		BBM	LBD4	MEL4	LOG2	ACR4	НАМЗ	WOX13	GH3.17 #	AT3G11280	APT1	SHR
PIN	SHP1	EXPA20	ADK2	CYCD2.1	CYCD6.1	CKX4	AHP6	AFB1	AFB2	ARR17	MELT	EGL3	HAM1	IAA2
JKD	IPT7	LBD18	ARR3	AHP3	ZF3	LBD33	NAP	AHK3	¢2FC	GL2	PUB4	HAM2	Анр2	AUX1
СОІІ	ABI8	AFBB	KMD2	KCS2	ARR12	Снзв	U-box	РНВ	WOE.AHK4	АНК1	PID2	KMD1	тмот	WOX14
MAIN	ARR7	CLV1.like3	IPTZ	KAN4	мава	PLT3	IAA19	CYCD1.1	JAZ1	ARF7	Тпи	HPT1	HUCS	LOGS
Stimulus	ADK	TAR2	MEL2	ARF1	CYCD3.1	MYB52	HAT22	ARR2	ARF18	ARR9	IPT6	RBR1	тмо5	LOC3
МҮВ56	BDL	LAX3	IAA18	тмоб	CRF2	PIN3	CUC3	KAN1	KRP2	PLT2	TAA1	IAA5	CLV1.like4	LOG7
E2FA	EXPA14	СҮР735А2	BAK1	CLE2	PID	IAA1	WAG1	LOG4	YUC3	ARF6	CK.N.GT	CRF6	PI	IAA28
LOCA	CRF11	RGF7	REV	AT5G06270	CRF3	APT5	ARR8	DPA	CH3 1	ARR23	CYP735A1	HDG12	ARF9	LOC9
AT1G04880	MYB53	ET4	CLV2	SCR	WAD2	IAA1B	ARF2	ETO1	TIR1	PLT1	Ск	CRF5	ADK1	AtWIP4
LBD29	U.box	LRP1	SHY2	🗧 рисні 🍃	ARR5	CLV1.like1	LBD16	IPT9	PINI	WKRY56	PCP19	CRF10	CKX1	GCN5
YUCS	SMB	MGP	PKL	bZIP8	LHW	RGF4								
												<b>X</b> Cy	tosca	ipe

Having validated our inference approach, we went forward with the network exploration

#### Topology of the LR GRN



Expert (i.e. by hand) analysis of the network structure revealed a modular organisation.



Having a look at some of the genes in those two modules...

What are their expression profile like?



Voβ *et al.,* 2015



Voβ et al., 2015







There appears to be biological meaning behing this modular topology

Can we investigate the dynamics of this patterning event (establishment of QC / definition of boundary)?
# Modeling GRN dynamics - PANTHEON

#### We wanted to investigate the precise dynamics of our GRN.



With several hundred of genes and interactions to consider and no already available solution to simulate such a system easily, we opted to develop our own software.

### Modeling GRN dynamics - PANTHEON

# PANTHEON

A Python -based Generic Boolean Network simulator

Based on Boolean formalism

Automatically model largescale genes network

Designed to work from simple network description (list of genes and interactions)

# Modeling GRN dynamics - PANTHEON

Initialize Network	
Import network	<u></u>
Gene List File	
	Browse
Network Structure File	
	Browse
Gene network Automated Initiation Algorithm (GAIA)	'
Number of nodes	
Number of interactions	
Run mode	
Batch Computation Mode O Visual Network Mode	
Import Cancel	8 Batch Mode
	Input : Lis

<u>GUI</u> : no need to code to simulate your gene network behavior

Import your network or generate a random one / Export simulation results as csv files

<u>Tools included :</u> in silico mutants study with a click among other things

<u>Modular structure :</u> base library of regulation models can be extended at will with your own

Input : List of genes	Input : Interactions in the network	Predict System Fates
AFB1	['ANT', '-1', 'IAA29']	Model type logical -
AFB2 AFB3	['ANT', '-1', 'YUC2']	Boundary conditions transient -
AHP6	[ANT', '1', 'CUC3']	Genes initial states random
ARF1	['ANT', '1', 'CYCD3.1'] ['ARF1', '-1', 'ARF1']	Number of initial states : O All possible states • Given number of states 1
ARF16 Ceses	[ARF1', '-1', 'EXPA14'] Dispetitives	KO mutation type none
ARF18	[ARF1, -1, 'BIN2']	List of KO genes
ARF19 ARF2	['ARF1', '-1', 'SCR'] ['ARF16', '-1', 'ARF4']	OA mutation type none
ARF4	['ARF16', '-1', 'GATA23']	List of OA genes
ARF7	['ARF16', '-1', 'AA11'] ['ARF16', '-1', 'IAA29']	Run PYTHONIS
ARF8	['ARF16', '-1', 'LBD17']	
AT3G11280	[ARF17', '-1', 'AFB3']	Automatically Research Genes Of Significance
ATML1 AUX1	['ARF17', '-1', 'AXR4'] ['ARF17', '-1', 'CDKB2 1']	Number of iterations 1
AXR4	['ARF17', '-1', 'CKX6']	Choose the models to run through ARGOS :
BAK1 BBM	['ARF17', '-1', 'CRF3'] ['ARF17', '-1', 'CUC3']	logical 📩 transient
BDL	['ARF17', '-1', 'EXPA20']	algebraic constant
BRI1	['ARF17', '-1', 'PHV'] ['ARF17', '-1', 'PLT3']	
CDKB2.1	['ARF17', '1', 'BAK1']	Run ARGOS
CLF	[ARF17, 1, IAA2] ['ARF18', '-1', 'ARF7']	
CLV1 CLV2	['ARF18', '-1', 'IAA28'] ['ARF18', '-1', 'IAA5']	Challenge Fates
CNA CNA	['ARF18', '-1', 'LBD17']	Placeholder - WIP algo
CRF1 CRF2	['ARF19', '-1', 'CLF'] ['ARF19', '1', 'AUX1']	Current Fate :
CRF3	['ARF19', '1', 'LBD16']	Targeted Fate :
	[AKFZ, -1, AHP6]	Run APOLLO
	PHAISTOS	
Back to files import Exit	which and the termination and the scalable. Your an est an inte	autor under Defensionen Stemmunger - Rich nämter auch

# PANTHEON - the LR dataset case study

Working on a subset of 134 genes / 495 interactions, full simulation of the network behavior using pure logical or algebraic model





Prediction of majority stable state corresponding to meristematic state (genes from module 2 active, genes from module 1 inactive)

# PANTHEON - the LR dataset case study

ARGOS Module - Mass *in-silico* mutagenesis and computation of a score of impact on network behavior for each gene (mean hammond distance between wild-type and mutants stable states for all model and mutation combinations)



ARGOS Module - Mass *in-silico* mutagenesis and computation of a score of impact on network behavior for each gene

Genes	mean distance for KO	Genes	mean distance for OA
PLT1	0.168600746	PLT7	0.346343284
ARF6	0.136735075	PUCHI	0.326567164
LRP1	0.13113806	CRF1	0.272742537
PHB	0.124869403	ARF2	0.248246269
TMO5	0.103973881	PLT5	0.245466418
SHR	0.098656716	ARF9	0.226529851
SCR	0.087817164	ARF17	0.179328358
SHP1	0.081100746	U.box	0.153955224
ATML1	0.063302239	ARF19	0.148022388
PID2	0.060970149	WRKY43	0.13369403

TOP10 predicted as most significant genes when KO or OA

# PANTHEON - the LR dataset case study



Most impactful genes when OA are in module 1 (early genes which we need to be repressed later on)

# PANTHEON - the LR dataset case study



Most impactful genes when KO are in module 2 (late genes which we need to be expressed for LRP development)

# LRP morphogenesis - In summary



📕 Epidermis 🔲 Cortex 🔲 Endodermis 🔲 Pericycle 🔲 Stele

Time after gravistimulation



Arabidopsis LR as an excellent model system of organogenesis : simple, controllable, accessible



Creation of the LRP database covering the full development of the organ



Creation of the TDCor algorithm and inference of the LRP development GRN

# LRP morphogenesis - In summary



Topological analysis revealed a modular structure tied to biological function and a possible bifurcation switch between flank/organizing center identities





Creation of an automated Boolean modeling software which predicted that the topology a the GRN was enough to generate a meristematic identity and was able to retrieve modular organization with no *a priori* 

Once now, back to biology to confirm the prediction of the model (i.e. working on generating and characterizing mutants...)

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Y. Boutté



J.-D. Faure F. Tellier





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Supporting agricultural research for sustainable development

#### **KANADI** transcription factor



WT

ats/kan4-1

# Roles of polarity determinants in ovule development

 ATS provides boundary maintenance and promotes the laminar growth of the inner ovule integument

Leon-Kloosterziel, et al., 1994; Mc Abee et al., 2006; Kelley et al., 2009





#### PISTILLATA expression is enhanced in *lhw* mutant

LRIS



3 independant biological replicats (n>50 seedlings/replicats), Student tests p\*\*\* < 0,01

#### Upstream regulators of PI as candidates genes for QC establishment

48h gravistimulation screening



■I ■II ■III ■IV ■V ■VI ■VII ■LR

#### Genes are organised into three main groups

Group 2





![](_page_53_Figure_4.jpeg)

![](_page_53_Figure_5.jpeg)

![](_page_53_Figure_6.jpeg)

54

#### Activation pattern of the ARF7 module in the primordium

![](_page_54_Figure_1.jpeg)

Lavenus et al., 2015 Hirota et al., 2007

LBD16

PUCHI

PLT5

![](_page_54_Figure_4.jpeg)

#### Gene patterns from transcriptomic LR dataset

![](_page_55_Figure_1.jpeg)

Time after gravistimulation

#### Gene patterns from transcriptomic LR dataset

![](_page_56_Figure_1.jpeg)

Time after gravistimulation

#### Gene patterns from transcriptomic LR dataset

![](_page_57_Figure_1.jpeg)

Time after gravistimulation

#### Genes are organised into three main groups

![](_page_58_Figure_1.jpeg)

#### Genes are organised into three main groups: example of PLETHORA family transcription factors

![](_page_59_Figure_1.jpeg)

#### Several network topologies could explain profile correlation

![](_page_60_Figure_1.jpeg)

Lavenus et al., (2015)

#### Activation pattern of the ARF5 subnetwork in the LRP

![](_page_61_Picture_1.jpeg)

#### pMP::MP:GFP

Du & Scheres, 2017

![](_page_61_Picture_4.jpeg)

Lavenus et al., 2015

# This is consistent with both temporal and spatial patterning in gene expression pattern

#### Transcript accumulation

![](_page_62_Figure_2.jpeg)

> The general topology of the network suggests a toggle-switch mechanism controlling a spatio temporal gene expression pattern in relation with root meristem establishment

#### Genes are organised into three main groups

![](_page_63_Figure_1.jpeg)

![](_page_63_Figure_2.jpeg)

![](_page_63_Figure_3.jpeg)

![](_page_63_Figure_4.jpeg)

#### The root apical meristem generates root primary tissues

![](_page_64_Figure_1.jpeg)

- Primary anatomical organization of roots is stereotyped.
- > Root meristem organized around a central stem cell niche
- > Arabidopsis thaliana as a simple plant model.

The soil and light environment plays a key role in lateral root (LR) positioning

![](_page_65_Figure_1.jpeg)

![](_page_66_Picture_0.jpeg)

- Uses any given predicted topology of a GRN (e.g. 246 genes, 1069 interactions)
- Boolean modeling as a simplification (various formats)
- Strong biological assumptions

• Strong upregulators

• Strong downregulators

 $\circ$  No lazy genes

![](_page_66_Picture_7.jpeg)

![](_page_67_Picture_0.jpeg)

- Uses any given predicted topology of a GRN (e.g. 246 genes, 1069 interactions)
- Boolean modeling as a simplification (various formats)
- Strong biological assumptions

• Strong upregulators

• Strong downregulators

 $\circ$  No lazy genes

![](_page_67_Picture_7.jpeg)

> Automated generation and solving of boolean model for entire network

#### A new simulation algorithm – **PYTHONIS**

(PYTHon-based bOolean Network generic Solver)

> For any random or given initial state,

 $\circ$  state flow (deterministic)

 $\circ$  final states (can be stable states or loops)

 $\circ$  basins of attraction

Hamming distance between basins of attractions

o => identification of nodes important for cell fate bifurcation?

50

10

20

Time after stimulus (h)

![](_page_68_Figure_8.jpeg)

#### A new simulation algorithm – **PYTHONIS**

(PYTHon-based bOolean Network generic Solver)

> For any random or given initial state,

 $\circ$  state flow (deterministic)

 $\circ$  final states (can be stable states or loops)

 $\circ$  basins of attraction

Hamming distance between basins of attractions

o => identification of nodes important for cell fate bifurcation?

50

10

20

Time after stimulus (h)

![](_page_69_Figure_8.jpeg)

#### A new simulation algorithm – **PYTHONIS**

(PYTHon-based bOolean Network generic Solver)

For any random or given initial state,

- $\circ$  state flow (deterministic)
- o final states (can be stable states or loops)
- $\circ$  basins of attraction
- Hamming distance between basins of attractions
- o => identification of nodes important for cell fate bifurcation?

Simulation of the impact of knock-out (always 0) or gain-of-function (always 1) mutations

impact on state flow and final states
Hamming distance between « mutant » and « wild type » final states
=> assessing the significance of each node in state flow

Currently being validated against known regulatory networks

#### Modeling dynamic properties of the inferred network

> Aim : to model dynamically the state flow of the gene network in order to identify gene regulatory cascades, master regulators, attractor states, bifurcation behaviours...

#### TDCore inputs

1	AT1G02850	BGLU11	0		1	"V1"	"V2"	"V3"	"V4"	"V5"
2	AT1G03430	AHP5	0		2	"AT1G01010"	7.82	7.66	7.57	7.48
3	AT1G03840	MGP 2			3	"AT1G01040"	7.06	7.29	7.27	7.09
4	AT1G04220	KCS2	0		4	"AT1G01050"	9.78	9.62	9.8 9.	93 9.
5	AT1G04240	SHY2	-1		5	"AT1G01060"	5.44	5.31	6.01	7.59
6	AT1G04550	BDL	-1		6	"AT1G01070"	9.33	9.08	9.06	8.82
7	AT1G04610	YUC3	0		7	"AT1G01080"	5.79	5.87	65.	94 5.
8	AT1G04880	AT1G04	880	2	8	"AT1G01090"	9.56	9.6 10.	75 11	.29 11
9	AT1G10470	ARR4	-1		9	"AT1G01100"	10.13	10.61	10.98	11.13
10	AT1G12820	AFB3	0		10	"AT1G01110"	4.18	4.33	4 4	3.94

#### **TDCor** outputs

1	source	inter	target	btstp	index	?
2	MGP -1	MGP 2.7	0 0	-		
3	MGP -1	SHY2	13.7	1.73	1.2	
4	MGP -1	ARR11	92.4	1.004	0.5	
5	SHY2	1 ARF1	1 4.2	1.85	4	
6	SHY2	-1 ADK2	2 17.2	2 1.6	77 1.5	
7	SHY2	-1 HAM1	100	0.856	0.5	
8	SHY2	-1 HAM3	3 94.9	9 1.5	04 0.5	
9	BDL -1	BDL 10.1	1 0	0		
10	BDL -1	MYC2	38.4	1.004	0.5	

Complex network e.g. 246 genes, 1069 interactions
## **Modeling dynamic properties of the inferred network**

> Strategy: to use boolean modeling of the network



# Modeling dynamic properties of the inferred network

> Strategy: to use boolean modeling of the network



However most available boolean models require explicit specification of network and of each interaction rules (BooleanNet, NetDS, NetworkToolkitExtended, BooleSim, SimBoolNet, Atalia, ...)

- → Impractical for massive network modelling
- Currently developing implementation of automated boolean modelling for large scale networks



Uses any given predicted topology of a GRN (e.g. 246 genes, 1069 interactions)

Boolean modeling as a simplification (various formats)

# The LR network is predicted to organize into two subnetworks with distinct crosstalk with auxin



Auxin signaling (DR5::GUS)



> Distinct crosstalks of each module with auxin distribution and signaling may contribute to progressive patterning of the lateral root primordium.

## Use of marker genes to monitor LRP functional patterning



## Use of marker genes to monitor LRP functional patterning



Figure 4. Expression pattern of selected reporter constructs during lateral root formation. Plasma membranes are labelled with WAVE131-YFP (A-D, F-I) or propidium iodide (E,J).

## **Gradual functional patterning of the LRP**



Critical changes in gene expression occur at stage I-II transition and stage IV (meristem formation phase), and early after emergence (expression of epidermis and root cap markers)

#### HDZIP III, KANADI transcription factors

#### Eshed et al., 2001, Current Biology

*KANADI* loss- and gain-of-function alleles suggest that fine regulation of these genes is at the core of polarity establishment. As such, they are likely to be targets of the *PHB*-mediated meristem-born signaling that patterns lateral organ primordia.



Model of polarity establishment in lateral organs

#### **KANADI** transcription factor

#### Izhaki et al., 2007, Development

#### KANADI and Class III HD-Zip Gene Families Regulate Embryo Patterning and Modulate Auxin Flow during Embryogenesis in Arabidopsis

Loss of KANADI activity in a Class III HD-Zip mutant background mitigates the defects in bilateral symmetry, implying that the two gene families act antagonistically during embryonic pattern

formation.



Materials:

- Mutant lines have been described previously: kan1-2 (Eshed et al., 1999); kan2-1 (Eshed et al., 2001); kan3-1, phb-6, phv-5, and rev-9 (Emery et al., 2003); kan4-3 (Mcabee et al., 2006)
- kan1-2 kan2-1 kan3-1 kan4-3 quadruple mutant
- kan1-2 kan2-1 kan4-3 phb-6 phv-5 rev-9 hextuple mutant

#### **KANADI** transcription factor

#### Kelley et al., 2009, Plant Journal

#### Roles of polarity determinants in ovule development

Class III homeodomain leucine zipper (HD-ZIPIII) genes CORONA (CNA), PHABULOSA (PHB) and PHAVOLUTA (PHV) are expressed adaxially in the inner integument during ovule development, independent of ABERRANT TESTA SHAPE (ATS, also known as KANADI4) activity. Loss of HD-ZIPIII activity can partially compensate for loss of ATS activity in the *ats cna phb phv* quadruple mutant, showing that CNA/PHB/PHV act in concert with ATS to control integument morphogenesis wild-type ats



<u>Materials</u>: - ats-3 phb-6 phv-5 rev-9/+

#### **KANADI** transcription factor

Gao et al., 2010, Plant Biotech journal

A new dominant Arabidopsis transparent testa mutant, sk21-D, and modulation of seed flavonoid biosynthesis by KAN4



Materials:

- KAN4 activation over-expression lines

#### Caggiano et al., 2017, eLife

#### Cell type boundaries organize plant development

Leaf orientation, morphology and position are pre-patterned by HD-ZIPIII and KAN gene expression in the shoot, leading to a model in which dorsoventral genes coordinate to regulate plant development by localizing auxin response between their expression domains.



#### Parizot et al., 2008, Plant Physiology

Quantitative losses in vascular bundle and pericycle heterogeneity appear intimately correlated: There is a concomitant loss of diarch and bilateral structures in *lhw* mutants.





#### Materials:

Ito et al., 2013, Development

LHW is required for proper asymmetric cell division to generate vascular initial cells as well as for the correct expression patterns of components related to auxin flow, such as PIN-FORMED 1 (PIN1), MONOPTEROS (MP) and ATHB-8, and ATHB-8 partially rescues the vascular defects of Ihw. These results suggest that LHW functions as a key regulator to initiate vascular cell differentiation in association with auxin regulation.



PIN1::PIN1-GFP

#### Materials:

- Ihw (?) expressing PIN1::PIN1-GFP; PIN1::YFP-nls; DR5::GFP

- estrogen-inducible LHW expressing DR5::GFP, PIN1::YFP-nls and MP::YFP-nls (same ?)

#### De Rybel et al., 2013, Developmental Cell

A TMO5/LHW bHLH heterodimer controls plant vascular development. The dimer is necessary and sufficient for triggering periclinal cell division. Overlapping transcription patterns localize TMO5/LHW activity





#### Materials:

- pLHW-n3GFP
- *Ihw* (SALK\_023629), and *II1* (SALK\_108940); *Ihw II1* double-mutant
- pLHW-LHW-YFP
- pRPS5A-LHW

#### Vera\_Sirera et al., 2016 Current opinion in Plant Bioogy



Active domains of key factors for vascular development in an Arabidopsis root apical meristem.



TDCor6.32\_output\_221018\_parallel - Copie\_cytoscape\_ Outgoing 2step PI 135 nodes, 496 edges 55 nodes, 136 edges



TDCor6.32\_output\_l\_gnp-18july29-copy\_ Undirected node PI 281 nodes, 1216 edges

18 nodes, 25 edges



TDCor6.32\_output\_l\_gnp-18july29-copy\_ Incoming 1step PI 281 nodes, 1216 edges

6 nodes, 9 edges



TDCor6.32\_output\_l\_gnp-18july29-copy\_ Incoming 2 step PI 281 nodes, 1216 edges

18 nodes, 46 edges



#### Lateral root development in Arabidopsis thaliana



Mallamy and Benfey, 1997; Casimiro et al., 2003; De Smet et al., 2007; Péret et al., 2012; Lucas et al., 2013; Du and Scheres, 2017; Goh et al., 2016

# Feeding GRN with spatial and temporal information result in robust spacing and patterning of developing LRP



Reference state flow for a given combination of model parameters (random initial state to final state)

Genes	Α	В	С	D	Ε	•••
Initial State 1	0	1	0	1	1	
Final State 1	0	0	1	0	1	

Reference state flow for a given combination of model parameters (random initial state to final state)

Genes	Α	В	С	D	Ε	•••
Initial State 1	0	1	0	1	1	
Final State 1	0	0	1	0	1	

Mutate 1 gene (KO or OA) and compute mutant final state

Genes	Α	В	С	D	Ε	
Initial State 1*	1	1	0	1	1	
Final State 1*	1	0	0	1	1	•••

Reference state flow for a given combination of model parameters (random initial state to final state)

Genes	Α	В	С	D	Ε	•••	
Initial State 1	0	1	0	1	1		
Final State 1	0	0	1	0	1		

Mutate 1 gene (KO or OA) and compute mutant final state

Genes	Α	В	С	D	Ε	•••
Initial State 1*	1	1	0	1	1	
Final State 1*	1	0	0	1	1	

Compute distance between ref final state and mutant final state e.g. : d = 0,75 (75% different)

Reference state flow for a given combination of model parameters (random initial state to final state)

Genes	Α	В	С	D	Ε	•••	
Initial State 1	0	1	0	1	1		
Final State 1	0	0	1	0	1		

Mutate 1 gene (KO or OA) and compute mutant final state

Genes	Α	В	С	D	Ε	•••
Initial State 1*	1	1	0	1	1	
Final State 1*	1	0	0	1	1	

Compute distance between ref final state and mutant final state e.g. : d = 0,75 (75% different)

#### ARGOS does this :

- For <u>each gene</u>,
- For <u>KO and OA</u>,
- For <u>all possible combinations of</u> <u>model parameters</u>,
- For a <u>set of initial states</u>

And return for each gene the mean of all distances for KO and OA

# Approach and example of application *in vivo*:

# PISTILLATA

# Understanding and manipulating functional organisation in developing LR primordia of *A. thaliana*



 $\rightarrow$  Identify and validate new candidates involved in QC formation

# Looking for a new quiescent Center marker gene, PISTILLATA:GFP (PI:GFP)



#### $\rightarrow$ PI : GFP expressed in the QC of primary root

Nawy et al., 2005

# Single-cell RNA Sequencing in root identified 12 quiescent center specific genes



#### → Confirms that PISTILLATA is a QC-specific gene

Denyer et al., 2019

#### **PI:GFP expression in the LR primordia ?**





#### → PI::GFP expressed in the QC of primary root AND lateral root

Nawy et al., 2005

#### PI:GFP signal appears following the quiescent center establishment



Voβ et al., 2015

AT5G20240: PISTILLATA (PI)

Floral homeotic gene encoding a MADS domain transcription factor. Required for the specification of petal and stamen identities.





PI : GFP expressed in the QC of primary root.

# No LR phenotype

#### **Upstream regulators of PI involved in meristem patterning ?**



PI

PLT1

#### Upstream regulators of PI involved in meristem patterning ?



Voβ et al., 2015

## KANADI (4) and HDZIP III (5) TFs play antogonists role in development

- Act antagonistically to each other to regulate organs patterning
  - To establish the bilateral symmetry during embryo patterning (auxin)
  - To coordinate leaf dorso-ventral patterning by spatiallized expression domains (auxin)
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Antagonists role during LR meristem patterning?

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  - To coordinate leaf dorso-ventral patterning by spatiallized expression domains (auxin)

Antagonists role during LR meristem patterning?





Leon-Kloosterziel, et al., 1994; Emery et al., 2003; Hawker et al., 2004; Mc Abee et al., 2006; Kelley et al., 2009; Caggiano et al., 2017

#### **PISTILLATA** expression seems to not be changed in kan4-1 during LRIS



1 biological replicats (n>50 seedlings/ technical replicats), Student tests p\*\*\* < 0,01



3-5 independant biological replicats (n>20 seedlings), Student tests p\*\* < 0,02



↓ g

ew lateral root

## kan4-1 and phb-11 show delayed LRPs



No difference morphologically



teral roo

### kan4-1 and phb-11 show delayed LRPs



3-5 independant biological replicats, Chi<sup>2</sup> test p\*\*\*<0,01

### Do kan4, phb, lhw mutations impact QC marker genes expression ?

#### **Next steps**



### Do kan4, phb, lhw mutations impact QC marker genes expression ?

