How do molecular networks control flower development?



Cell identities are associated with molecular steady states



Development can be seen as a succession of molecular steady states evolving through time

Very important point: this system is self-organised

1-Same interaction network in all the cells

2-Communication between cells affect the state of the network



Objective: construct a MRN which is coherent with expression patterns and long range interactions



behavior

structure

1 - Interaction database(~300 papers)

- direct molecular interactions
- induction evidence
- genetic interactions (can be direct or not)

2- Expression database > atlas > molecular states



Superimposition

35 sepal genes projected (flower bud stage 3)



Sepal primordium : 6 molecular states with 35 elements

	Zone 1	Zone 2	Zone 3	Zone 4	Zone 5	Zone 6	
AGO1	1	1	1	1	1	1	
AGO7	1	1	1	0	0	0	
AGO10	1	1	1	0	0	0	
AHP6	1	1	1	1	1	1	
ANT	1	1	1	1	1	1	
AP1	1	1	1	1	1	1	
AP2	1	1	1	1	1	1	
ARF4	0	0	0	1	1	1	
AS1	1	1	1	1	0	0	
AS2	1	1	0	0	0	0	
AtHB8	0	0	0	1	0	0	
AUX1	1	0	0	0	1	0	
BARD1	1	1	1	1	1	1	
BOP2	1	1	0	0	0	0	
CNA	1	1	1	0	0	0	
DRNL	1	1	1	1	1	1	
ETT	0	0	0	1	1	1	
FIL	0	0	0	1	1	1	
JAG	0	0	1	1	0	1	
KAN1	0	0	0	0	1	1	
LFY	1	1	1	1	1	1	
LUG	1	1	1	1	1	1	
MiR165/166	0	0	0	1	1	1	
MiR390	1	1	1	1	1	1	
MP	1	1	1	0	0	0	
РНВ	1	1	1	0	0	0	
PHV	1	1	0	0	0	0	
PID	1	1	1	1	1	1	
PIN1	1	0	0	1	1	0	
REV	1	1	1	0	0	0	
STIP	0	0	0	1	1	1	
STY1	1	1	1	1	1	1	
SYD	1	1	1	1	1	1	A hand a start of the start of
TAS3	1	1	1	0	0	0	
YUC4	1	1	1	1	1	1	

3- Candidate molecular interaction graph



Theoretical requirements

- close circuits
- inputs

3- Candidate molecular interaction graph



ad

Expected behavior of our network



	Zone 1	Zone 2	Zone 3	
	Adaxial	Vascular	Abaxial	
AGO1	1	1	1	
AGO10	1	0	0	
AGO7	1	0	0	
ANT	1	1	1	
ARF4	0	1	1	
AS1	1	1	0	
AS2	1	0	0	
ETT	0	1	1	
FIL	0	1	1	
KAN1	0	0	1	F VT
MiR165/166	0	1	1	
MiR390	1	1	1	
REV	1	0	0	
TAS3	1	0	0	

A mathematical model is required Boolean logic has been used

4- Parameter values inferred from expression data > solution(s)

Behavior expressed as an activation function



A solution is represented by a set of activation functions

47 solutions were found

	Zone 1	Zone 2	Zone 3				
	Adaxial	Vascular	Abaxial				
AGO1	1	1	1				
AGO10	1	0	0				
AGO7	1	0	0				
ANT	1	1	1				
ARF4	0	1	1				
AS1	1	1	0	X			
AS2	1	0	0				
ETT	0	1	1				
FIL	0	1	1	ALA P			
KAN1	0	0	1				
MiR165/166	0	1	1				
MiR390	1	1	1				
REV	1	0	0				
TAS3	1	0	0				
Steady states							



Structure

5- Model validation



37 genetic interactions used to test the dynamics of the MRNs

Model predictions



Experimental observations

35 (out of 37) indirect interactions predicted by the model were supported by experimental observations

The 47 solutions were all equally good

The Plant Cell (2011) La Rota et al.



If we considere this network as the reference

Can we infere this network (or a resembling one) from transcriptomic data?

Among the different methods used to infer networks, which ones performs the best, which kind of information is obtained ?

Matériel utilisé

Données transcriptome issues de la plateforme transcriptomique de l'URGV.

- Même protocole expérimentaux pour toutes les comparaisons
- Même analyses statistiques pour la normalisation et l'analyse différentielle
- Stockage et gestion des données dans CATdb

Permet de

- garantir une certaine homogénéité du jeux de données
- retourner "assez facilement" à la description expérimentale de chaque expérience



La puce CATMA: évolution au cours du temps mais sur toutes les versions présence de 24576 sondes pour plus de 22K genes



Les versions correspondent à des ajouts de sondes. En particulier pour étudier les Petits ARNs

Conséquences: données manquantes non aléatoires pour certains gènes car inclus sur la puce dans les plus récentes versions seulement

Description d'une comparaison entre 2 conditions

- Puce 2 couleurs et expérience faite en dye-swap
- Au moment de l'analyse d'image, retrait des sondes ayant un signal non conforme (expertise humaine) → données manquantes au hasard
- Normalisation par lowess, correction d'un effet bloc -> obtention d'un log-ratio
- Partage de la correction pour obtenir une intensité par échantillon : I.ref, I.sample
- Analyse différentielle : variance comune calculée à partir des sondes ayant une variance de la différence d'expression non extrême. Ajustement de la pvalue par Bonferroni.

Extraction de CATdb

- Toutes les données publiques le 21 juin 2013 : 2171 comparaisons donc 4342 échantillons disponibles
- Information concernant les comparaisons
 - Organe : 32 modalités avec 4 principales (aerial, rosette, roots, whole plant)
 - Stade de développement : 82 stades
 - L'écotype : 40 dont 1077 columbia
 - Le génotype : 486 modalités
 - Présence de mutation : 4 modalités (yes/no, no, yes, no/yes) : 1083 no

Data 1

- 38 selected probes annotated with an AtG ID corresponding to 28 genes in ref. network.
- 1,558 selected experiments among 2,171 according to sample origin (e.g. 'Leaf', 'whole plant' YES whilst 'Root', 'cell culture' NO)
- \rightarrow compatibility of plant physiology with organ (sepal) polarity ?
- . Data was standardised.



Data 2

•Problem with NA's \rightarrow data imputation or discarding experiments with missing values because they are not missing at random



21(/37) probes have missing values, 3 with ~half are missing,
17 with ~1/3 missing and 1 with 1/10th missing
Roughly (less than) half of the experiments have no missing data but 15% have missing values for 3 genes only and
35% have over 20 missing measures (over 37)

Discrete Bayesian network

Static Bayesian networks (Friedman et al., Plos comput. bio., 2000)

- Directed Acyclic Graph (DAG)
- * Conditional probability distribution of X_i , given its parents Pa_i in $G:P_G(X_i/Pa_i^j) = \theta_i^j$

(independence of these local probabilities)



Graphic representation of a joint probability distribution:

$$P_G(X) = \prod_{i=1}^n P_G(X_i/Pa_i)$$

Probability Distribution for the Alarm Node given the events of "Earthquakes" and "Burglaries"					
Е	В	P(A E,B)	P(!A E,B)		
E	В	0.90	0.10		
Ε	! B	0.20	0.80		
! E	В	0.90	0.10		
! E	! B	0.01	0.99		

Gaussian graphical model

- X ~ N(0,Σ), Σ or more specifically Σ⁻¹ encodes direct relationships between probes.
- Data (samples) assumed iid.



Bootstrap

- Counts of |partial corr.| > |random partial corr.|
- in an augmented Σ^{-1} over n_{boot} =10,000 bootstrap repeats (stability with n_{boot} =1,000, slightly more stringent).
- Keep edges having counts = n_{boot} .

 \rightarrow list of ~50 edges (between probes).

Group of genes

- Merge genes known to have similar targets
 - [REV, PHB, PHV, CNA] = REV
 - [KAN1, KAN2] = KAN
 - [TAS3, RDR6] = TAS3
- Complex of proteins
 - [AGO1_miR165/166] = miR165/166
 - [AGO7_miR390] = miR390
 - [DRNL_REV] = REV
 - [AS1_AS2] = AS2

Resulting in 16 classes for 28 transcripts/probes

Direct interaction graph in sepal



GGM with bootstrap



Bayesian Network with bootstrap





Open questions

- Experiment selection: how is it linked to the reference network ?
- Elements of the network not included in the data ?
- Other inference methods ? But why would the tested 2 produce so different results: complementarity or (very) noisy predictions ?
- Room for causal inference from obs. Data ?