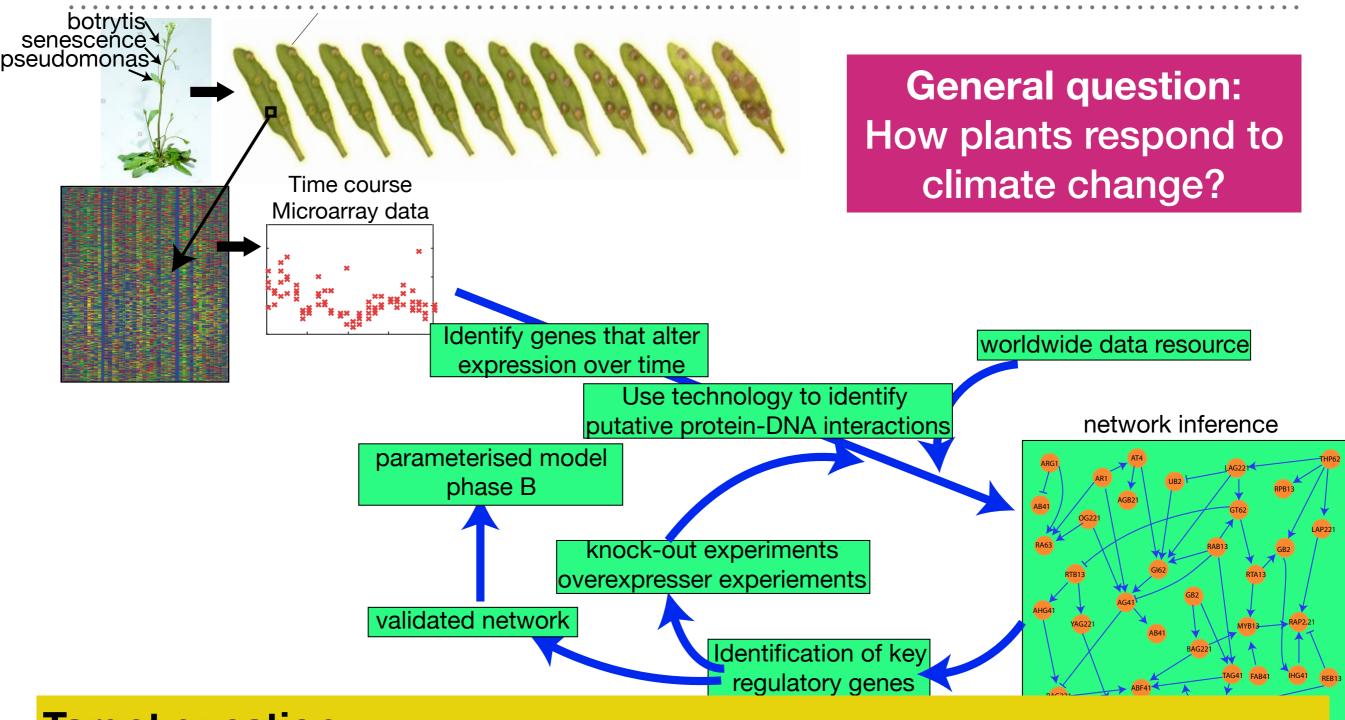
INFERRING TRANSCRIPTION LOGIC FROM MULTIPLE DYNAMIC **EXPERIMENTS**

Giorgos Minas, School of Mathematics & Statistics, University of St-Andrews, Scotland @Barcelona, 09.07.2018



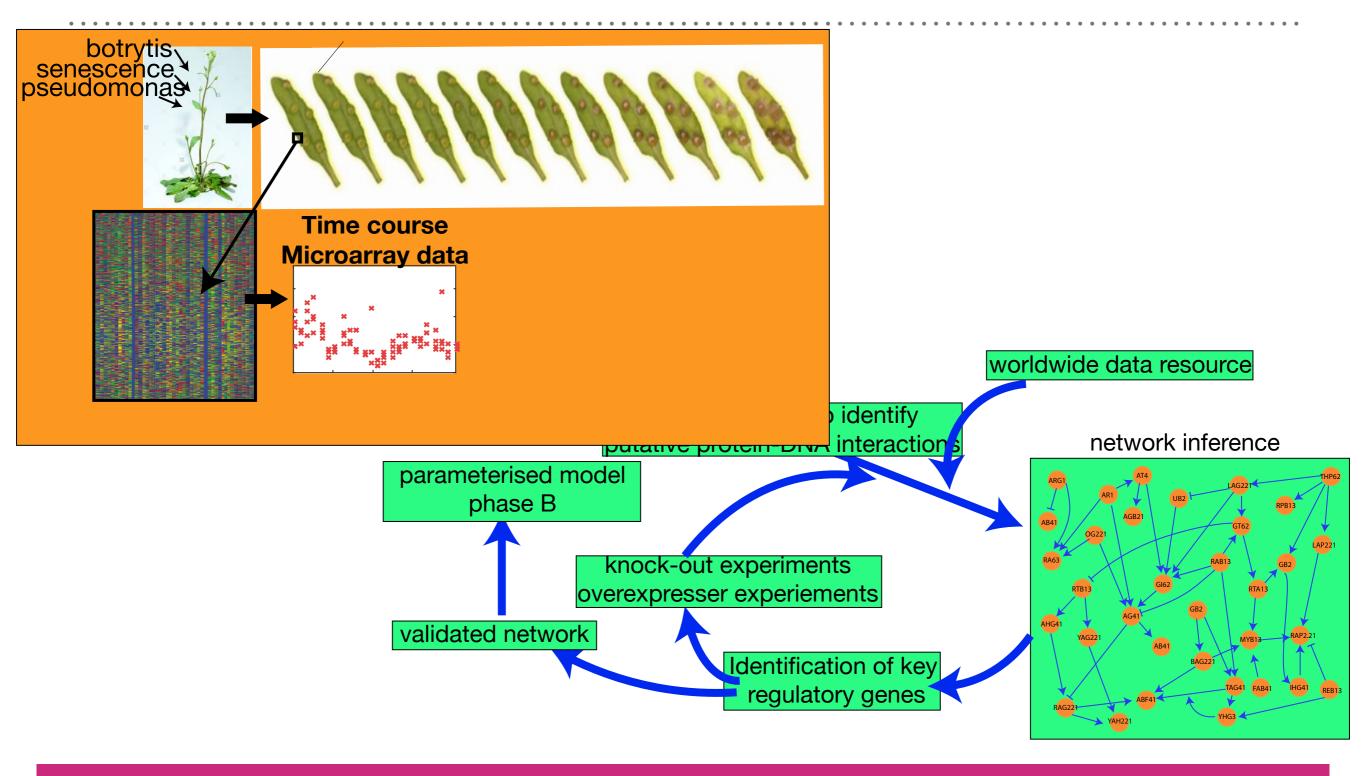
PLAN OF THE TALK

- Predicting Responses under Environmental Stresses in A. thaliana
- Transcriptional Regulation
- TR modelling
- TR Switch modelling
- Statistical inference for **TRS**

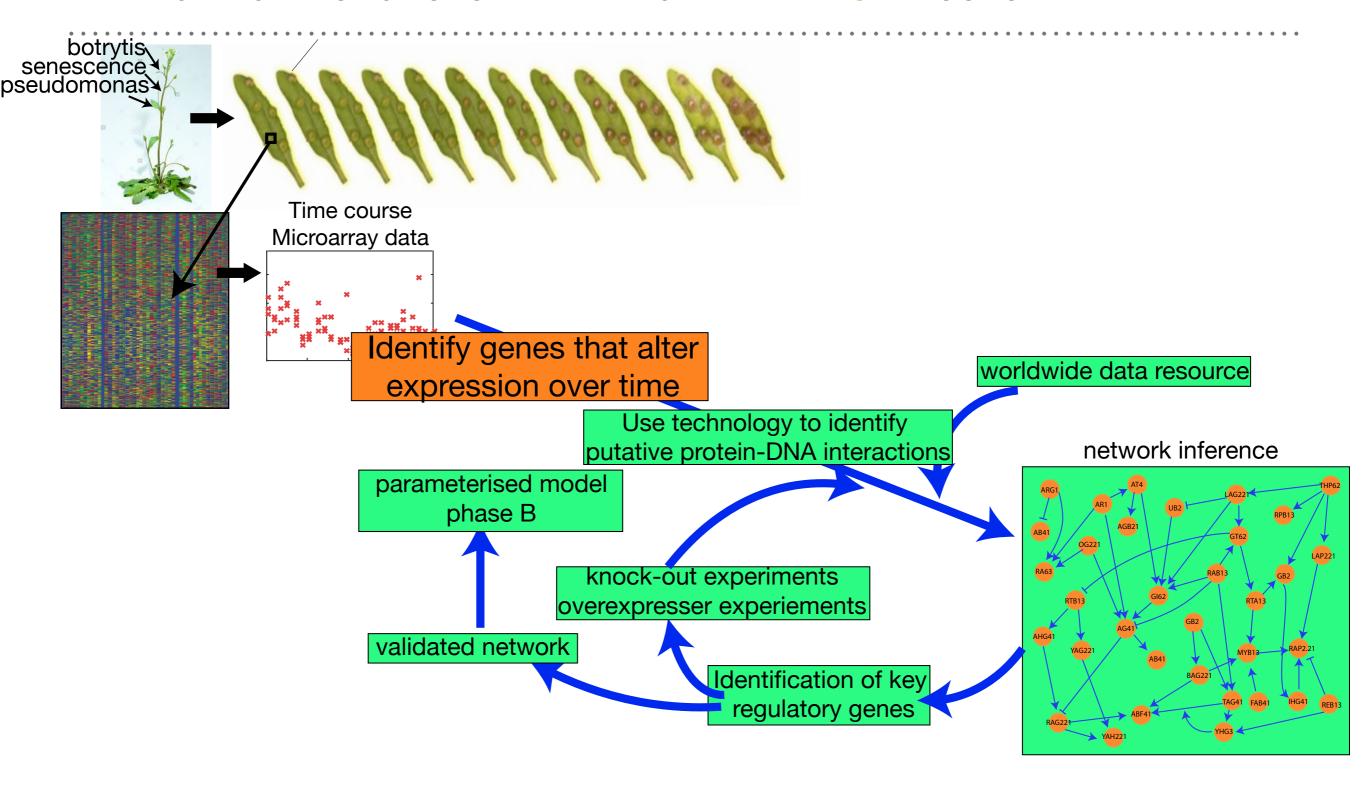


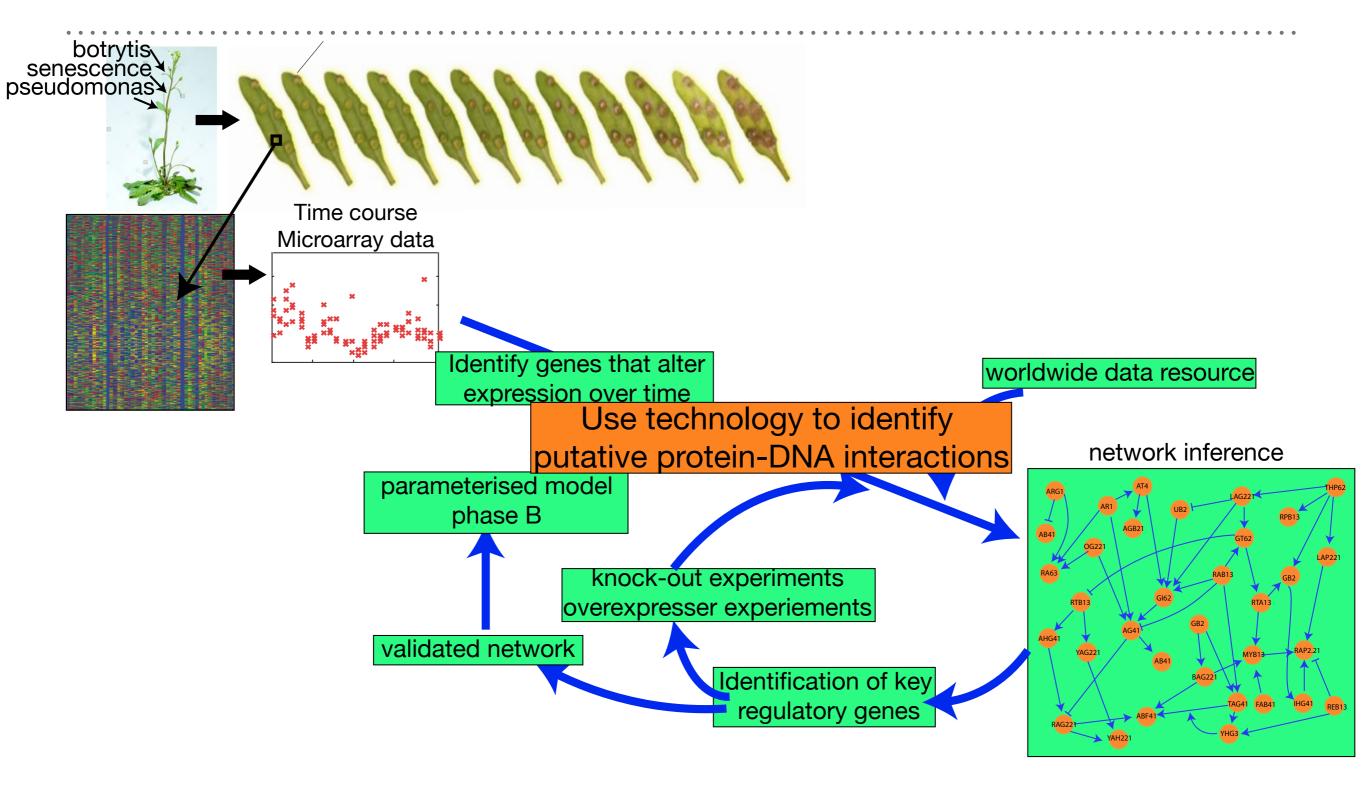
Target question:

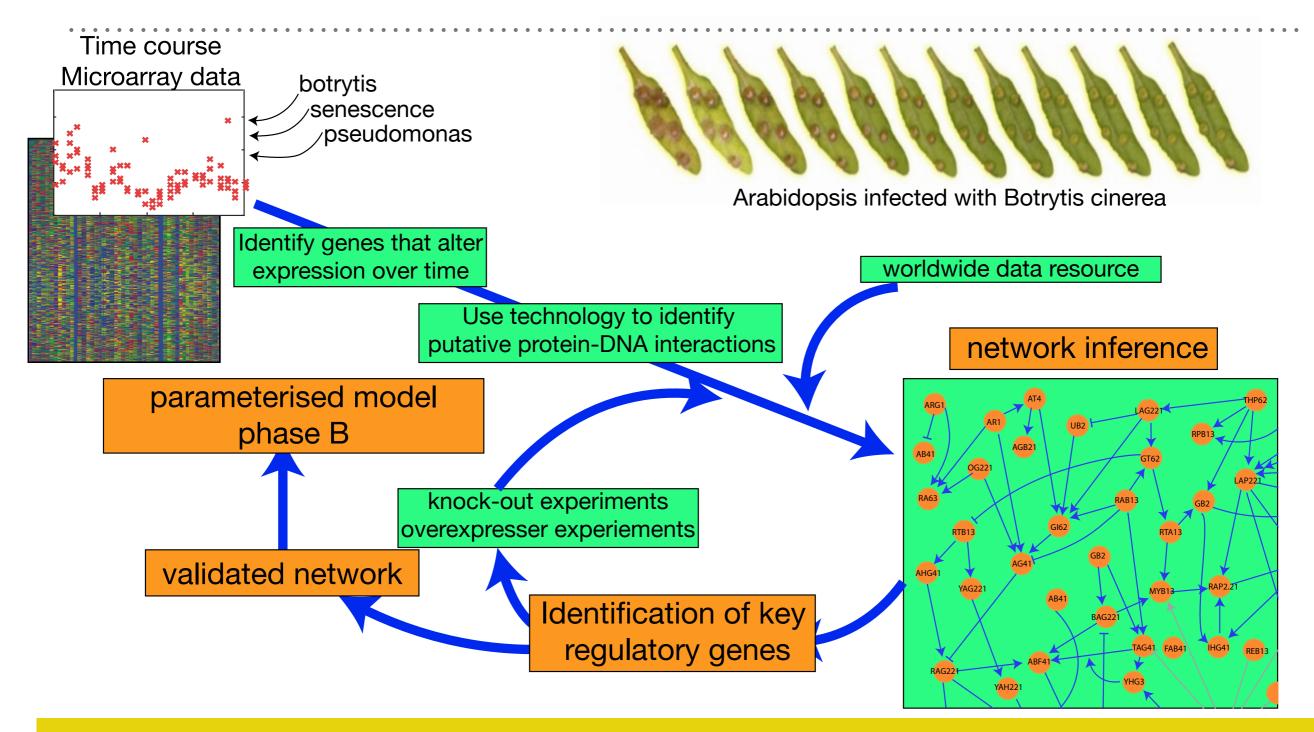
What gene regulation networks are active under environmental stresses? Which are the key genes for the response to stresses?



- Observe plants under various environmental stress
- Measure gene expression (microarray) in multiple time-points



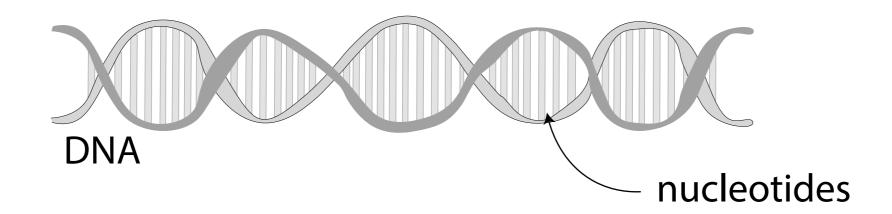




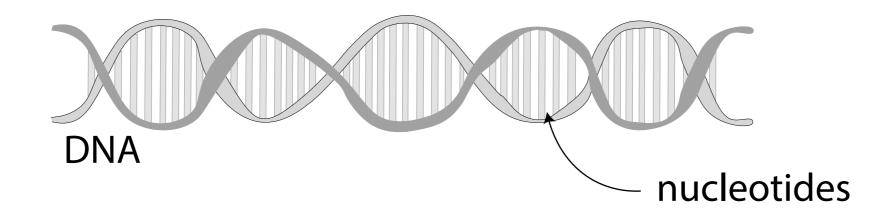
My part:

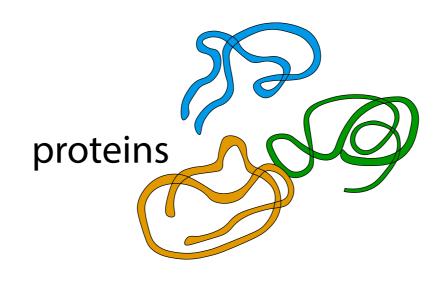
Develop a model of transcription regulation between the genes that are identified to be active and important under the stresses.

FROM GENES TO PROTEINS

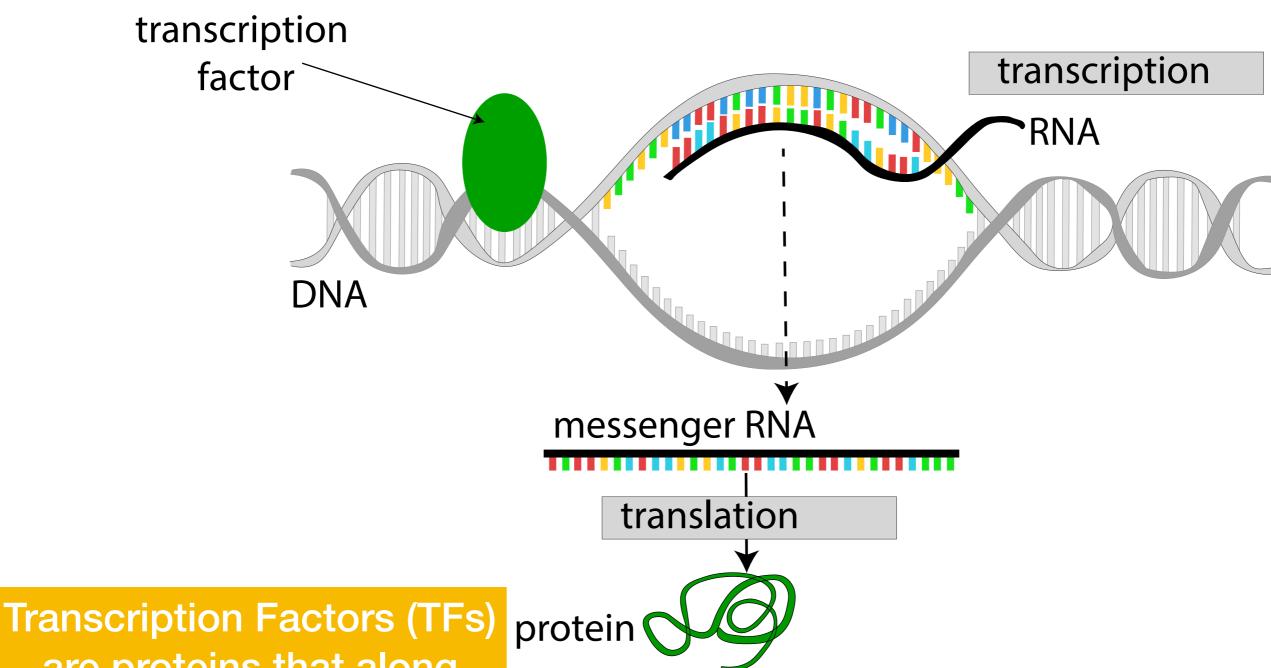


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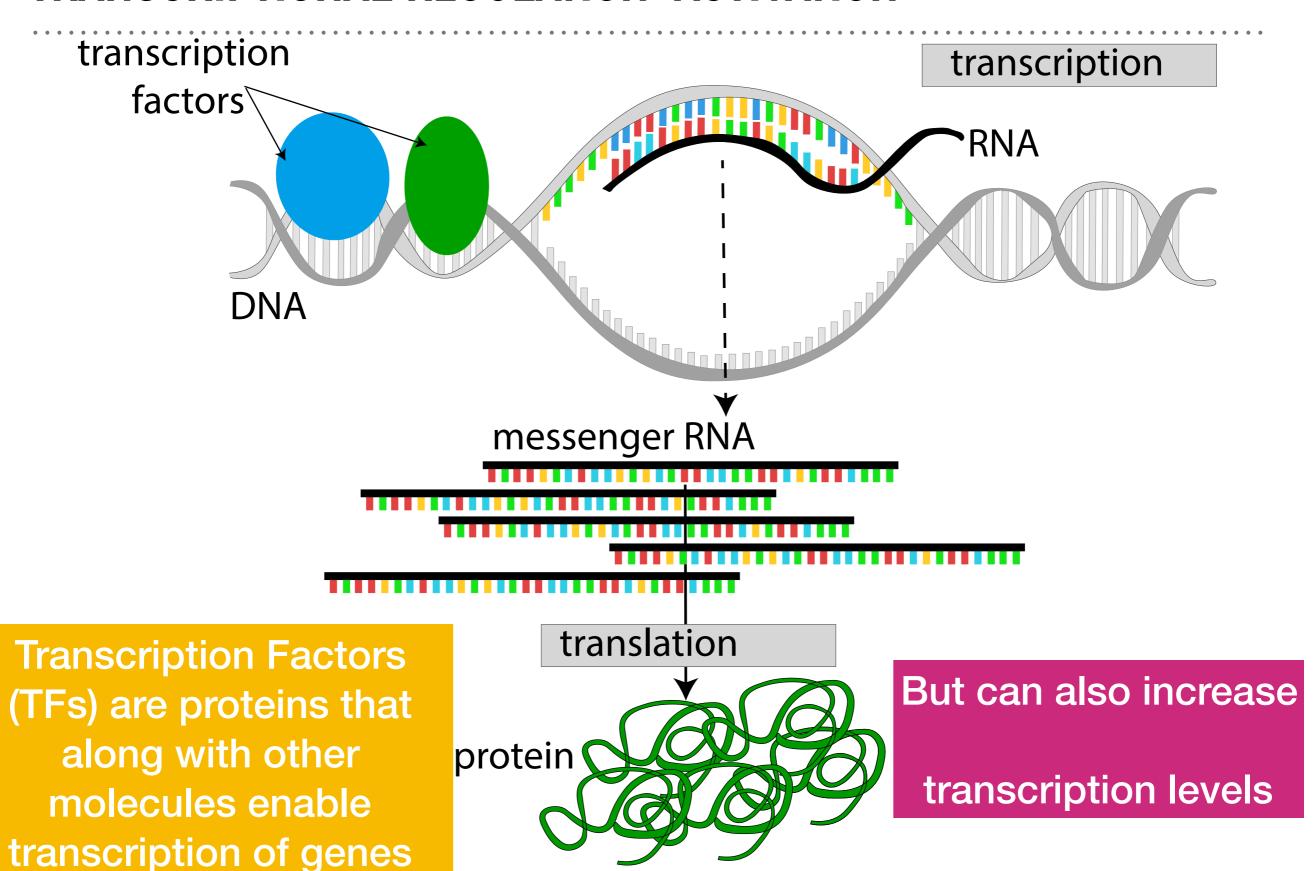


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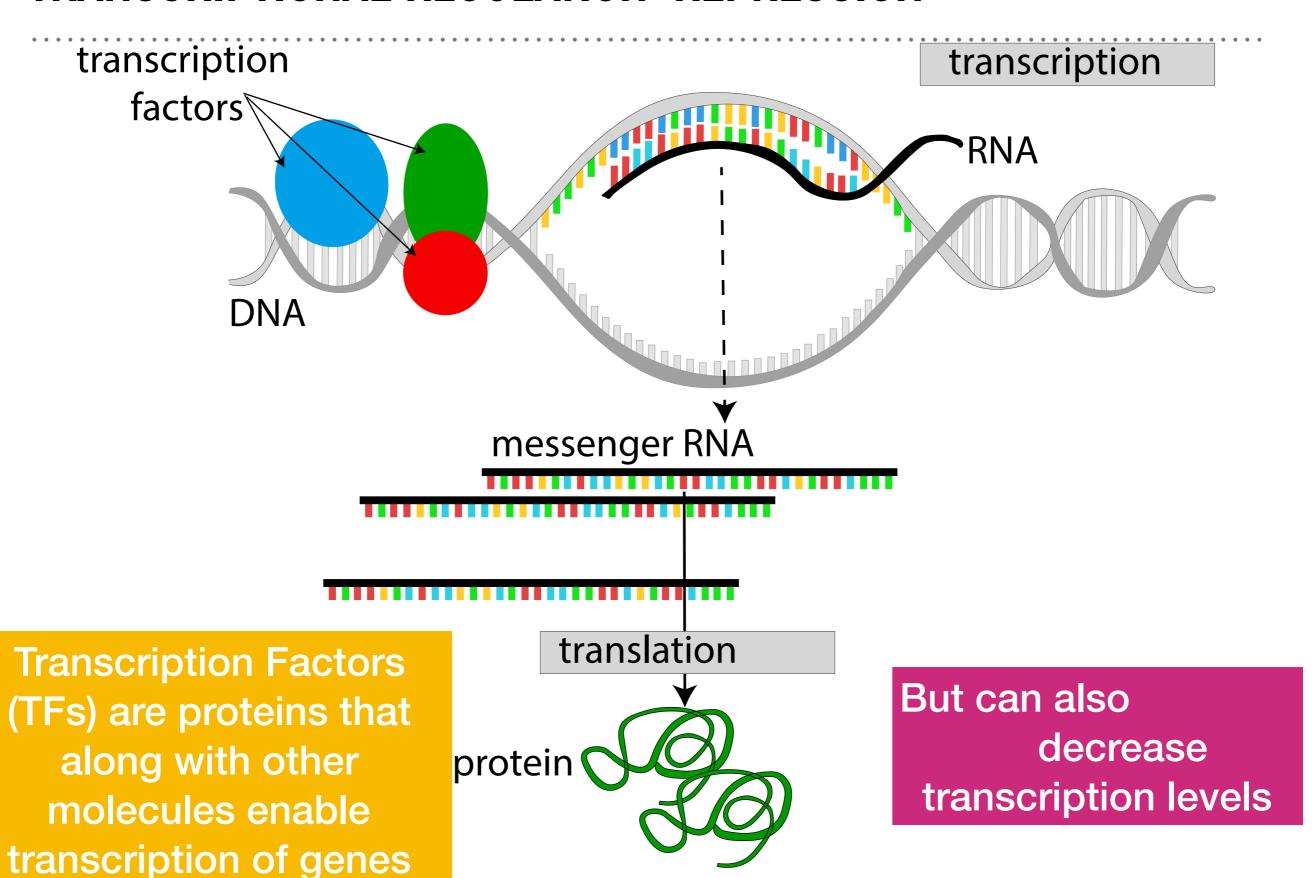


are proteins that along with other molecules enable transcription of genes

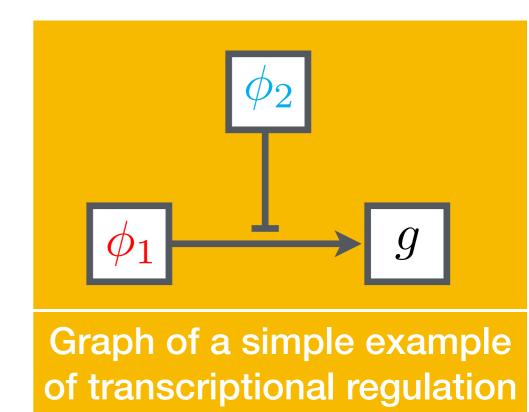
TRANSCRIPTIONAL REGULATION-ACTIVATION



TRANSCRIPTIONAL REGULATION-REPRESSION



➤ A large number of different models for dynamic & static observations, and for binary, discrete & continuous state spaces.



- ➤ A large number of different models for dynamic & static observations, and for binary, discrete & continuous state spaces.
- For dynamic (time-series) observations with continuous \mathbb{R}^+ state space, the mRNA expression is often modelled as the ODE

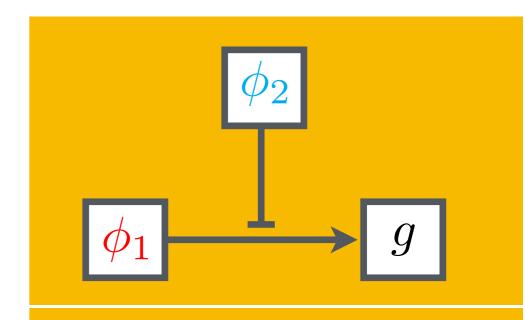
$$\frac{dM}{dt} = \tau(t) - \delta M(t)$$

 $\tau(t)$: transcription (birth) rate

 δ : degradation (decay) rate

which can be also written in regression form,

$$M(t) = M(0) + f(t, \tau, \delta)$$



Graph of a simple example of transcriptional regulation

For dynamic (time-series) observations with continuous \mathbb{R}^+ state space, the mRNA expression is often modelled as the ODE

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 $\begin{array}{c} \phi_2 \\ \hline \phi_1 \\ \end{array}$

where some of the models used for transcription are

Graph of a simple example of transcriptional regulation

$$\tau(t) = \alpha_0 + \alpha_1 P_{\phi_1}(t) + \alpha_2 P_{\phi_2}(t) + \dots$$

$$\tau(t) = \alpha_0 + \alpha_1 P_{\phi_1}(t) + \alpha_2 P_{\phi_2}(t) + \alpha_{12} P_{\phi_1}(t) P_{\phi_2}(t) + \dots$$

$$\tau(t) = \alpha_0 + \alpha_1 f_1(P_{\phi_1}(t), \theta_1) + \alpha_2 f_2(P_{\phi_2}, \theta_2)(t) + \dots$$

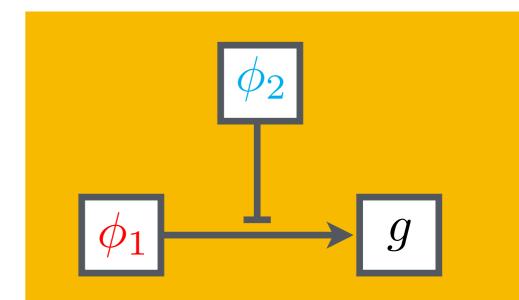
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Challenges: interpretability, identifiability, speed, accuracy/fit to data

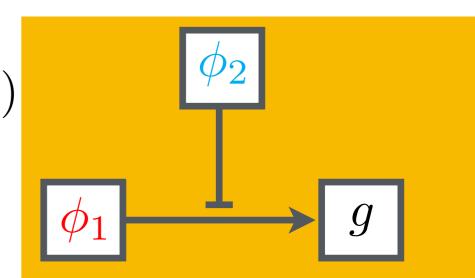
For dynamic (time-series) observations with continuous \mathbb{R}^+ state space, the mRNA expression is often modelled as the ODE

(experiment)
$$\frac{dM^{(k)}}{dt} = \tau^{(k)}(t) - \delta M^{(k)}(t)$$

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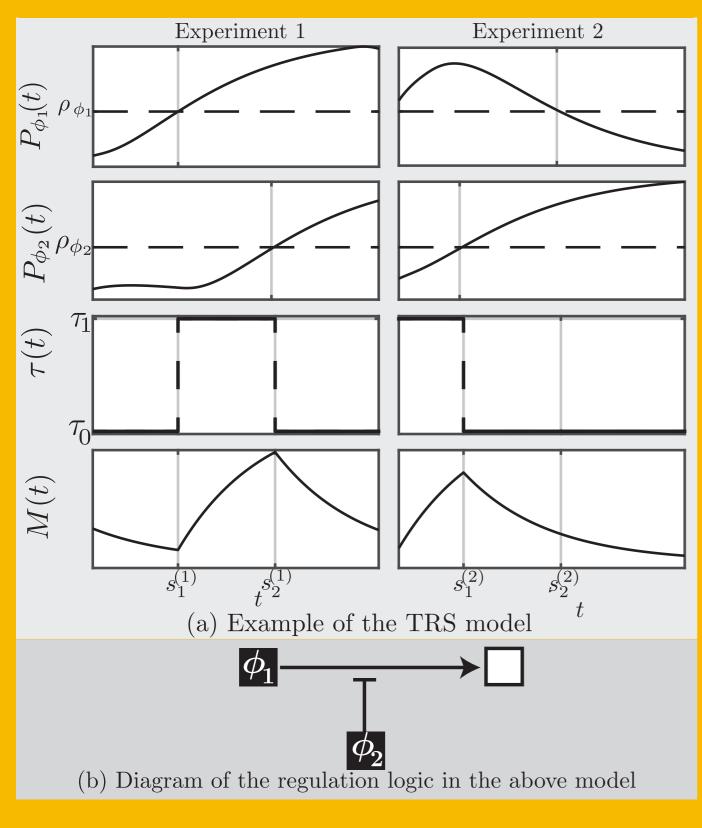
Graph of a simple example of transcriptional regulation

$$\tau^{(k)}(t) = \alpha_0^{(k)} + \alpha_1^{(k)} P_{\phi_1}^{(k)}(t) + \alpha_2^{(k)} P_{\phi_2}^{(k)}(t) + \dots$$

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$$\tau^{(k)}(t) = \alpha_0^{(k)} + \alpha_1^{(k)} f_1^{(k)} (P_{\phi_1}^{(k)}(t), \theta_1^{(k)}) + \alpha_2^{(k)} f_2^{(k)} (P_{\phi_2}^{(k)}, \theta_2)(t) + \dots$$

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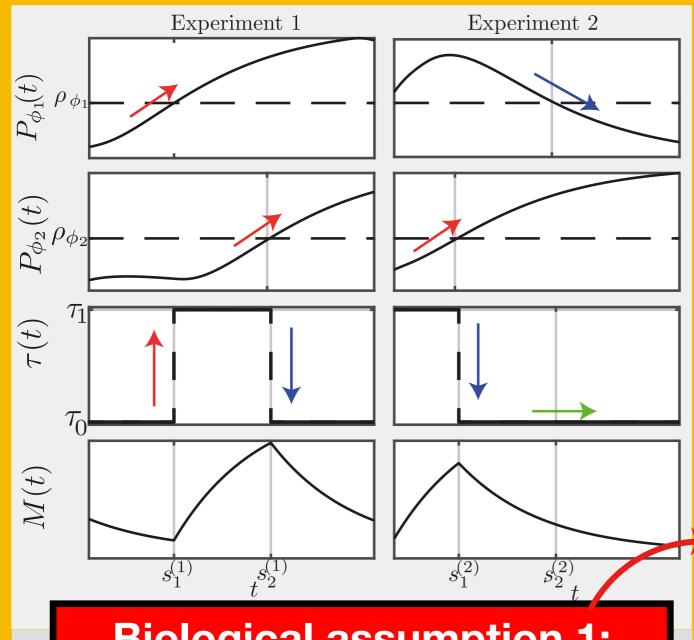


• The mRNA expression of the target gene

$$\frac{dM^{(k)}}{dt} = \tau(t) - \delta M^{(k)}(t)$$

where the transcription rate
$$au_0, \quad t \in [0,s_1], \ au_1, \quad t \in [s_1,s_2), \ dots \ au_q, \quad t \in [s_q,s_{q+1}],$$

- The switches s_i occur when one of regulators $\phi_1, \phi_2, \ldots, \phi_n$ crosses its threshold ρ_{ϕ_i} .
- The τ -rates are forced to be the same in time-intervals where all regulators are at the same activation state



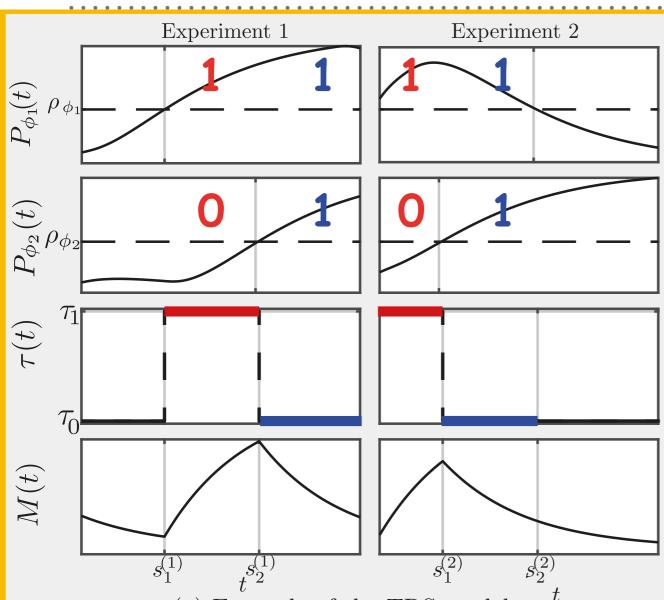
Biological assumption 1: transcriptional switches are caused by large changes in the TF's levels

• The mRNA expression of the target gene

$$\frac{dM}{dt} = \tau(t) - \delta M(t)$$

$$au(t) = egin{cases} au_0, & t \in [0,s_1], \ au_1, & t \in [s_1,s_2), \ dots & dots \ au_q, & t \in [s_q,s_{q+1}], \end{cases}$$
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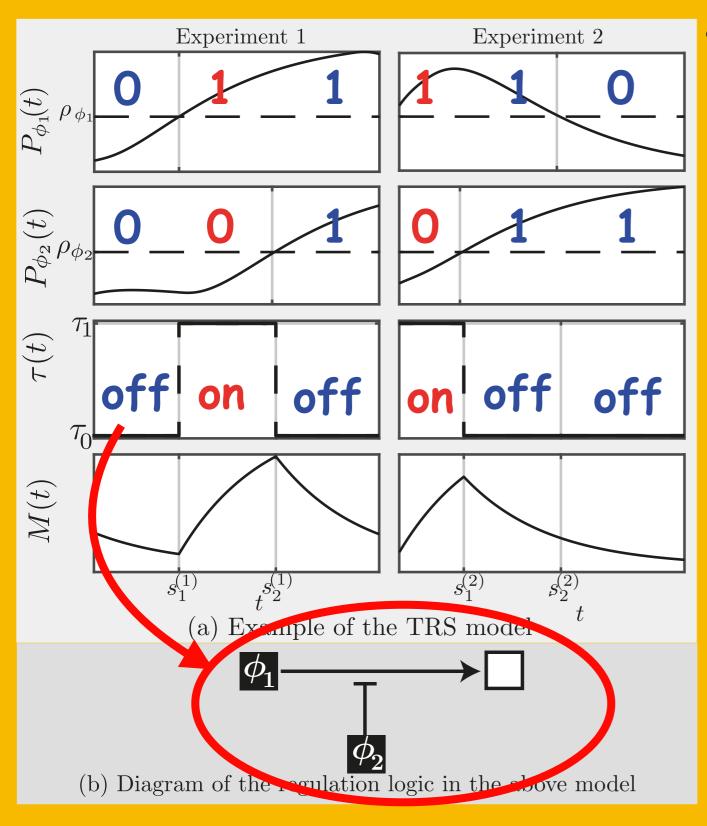


Biological assumption 2: The gene network is always the same. Different parts of the network may be active in different times & conditions. • The mRNA expression of the target gene

$$\frac{dM}{dt} = \tau(t) - \delta M(t)$$

$$\tau(t) = \begin{cases} \tau_0, & t \in [0, s_1], \\ \tau_1, & t \in [s_1, s_2), \\ \vdots & \vdots \\ \tau_q, & t \in [s_q, s_{q+1}], \end{cases}$$

- The switches s_i occur when one of regulators $\phi_1, \phi_2, \ldots, \phi_n$ crosses its threshold ρ_{ϕ_i}
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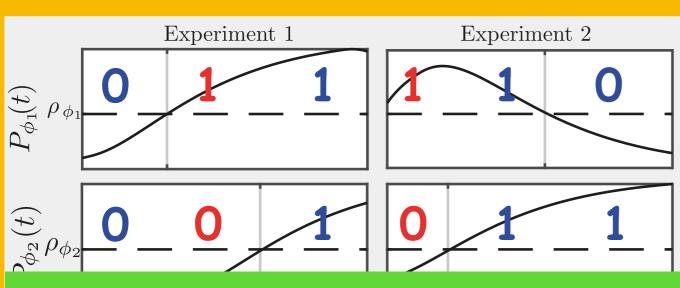
• The mRNA expression of the target gene

$$\frac{dM}{dt} = \tau(t) - \delta M(t)$$

where the transcription rate

The TRS model targets biologically interpretable descriptions of gene regulation

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• The mRNA expression of the target gene

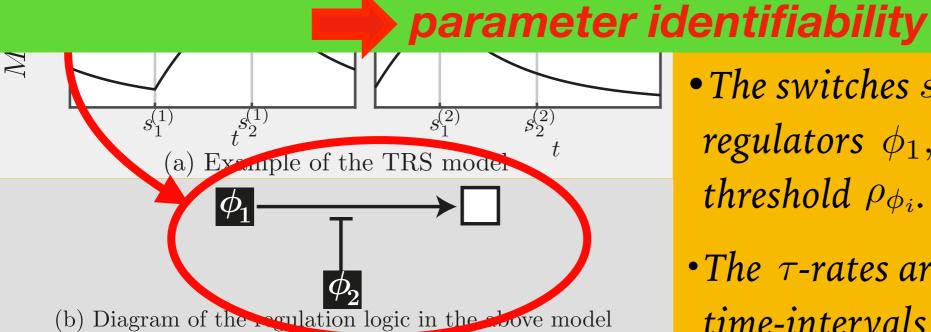
$$\frac{dM}{dt} = \tau(t) - \delta M(t)$$

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$$(\tau_0, t \in [0, s_1],$$

The model can be written as a linear regression with coefficients the τ -rates of ONLY the *observed* TF states $\alpha_1, \alpha_2, \ldots, \alpha_q$

$$M(t) = M(0)f_0(t,\delta) + \tau_{\alpha_1}f_1(T_{\alpha_1},\delta) + \dots + \tau_{\alpha_q}f_q(T_{\alpha_q},\delta)$$



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The model extends to multiple experimental conditions

$$Y_j(t) = M_j(t) + \epsilon_j(t)$$

 $j = 1, 2, \dots, J \text{ (experiment)}$

- ➤ The parameter vector includes
 - > number of regulators
 - ➤ identity of regulators
 - > their activation threshold
 - \triangleright and the τ -rates

which imply the regulation mechanism

• The mRNA expression of the target gene

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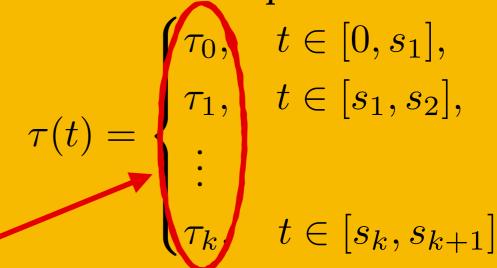
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➤ We use a trans-dimensional RJMCMC algorithm to infer the parameters

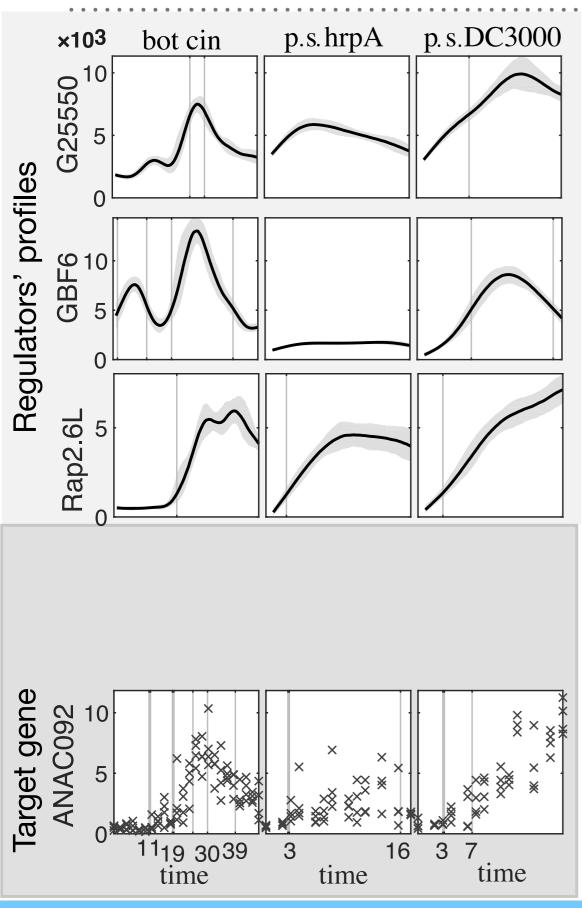
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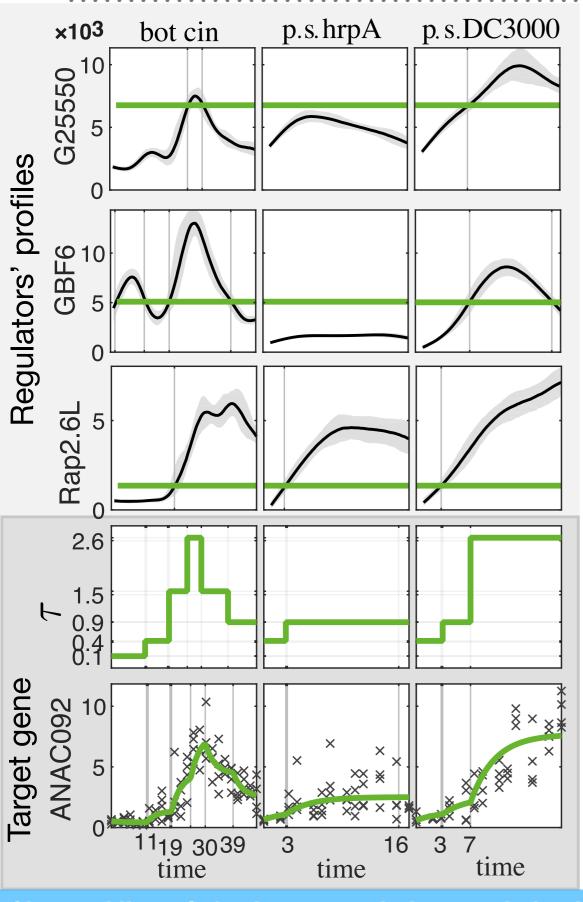
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APPLICATION OF TRS TO A. THALIANA MICROARRAY DATA



- Microarray (time-series) data:
 - ➤ Three experimental conditions
 - ➤ Four replicates
 - ➤ Twenty candidate regulators

APPLICATION OF TRS TO A. THALIANA MICROARRAY DATA



- TRS can infer the parameters and unravel biologically interpretable mechanisms that are consistent across multiple experiments.
- ➤ Good balance between model interpretability and model identifiability
- ➤ Output: posterior probabilities for all possible regulation models

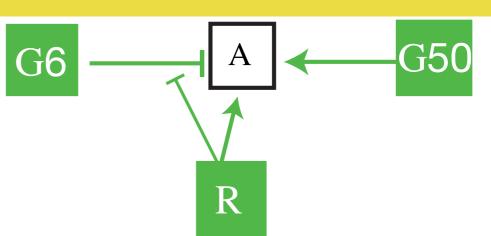
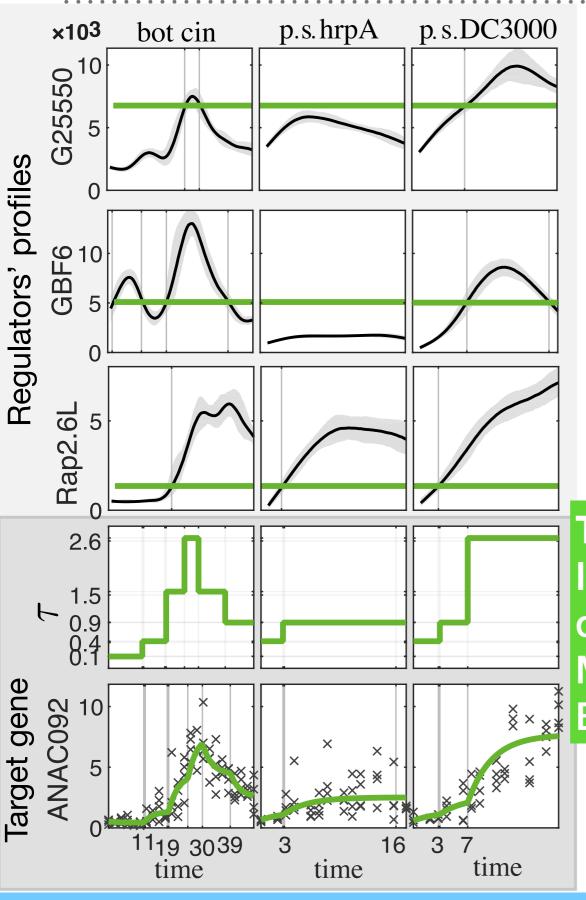


Diagram of the *a posteriori* most likely regulation mechanisms

APPLICATION OF TRS TO A. THALIANA MICROARRAY DATA



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TRS Method published in: Inferring transcriptional logic from multiple dynamic experiments, Minas G, Jenkins D, Rand D, Finkenstadt B Bioinformatics, 33, 21 (2017)

TRS software:

implemented in MATLAB available at https://github.com/giorgosminas/TRS

INSTEAD OF SUMMARY

Data Driven Approaches Hypothesis-driven approaches Mechanistic models

more data

more simple models

more complex models

more knowledge

PCA
Correlation networks
Multiple testing
Penalized Likelihoods
Clustering

Reaction Networks Markov processes

ODEs Bifurcation theory Catastrophe theory

Guide RN

Bayesian Networks

Boolean networks arget Sequence

PDEs

Gaussian Processes regression models

ABC MCMC

MCMC

Information Theory

Collaborators:

Dafyd Jenkins David Rand

Barbel Finkenstadt

Katherine Denby

Sponsors:



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