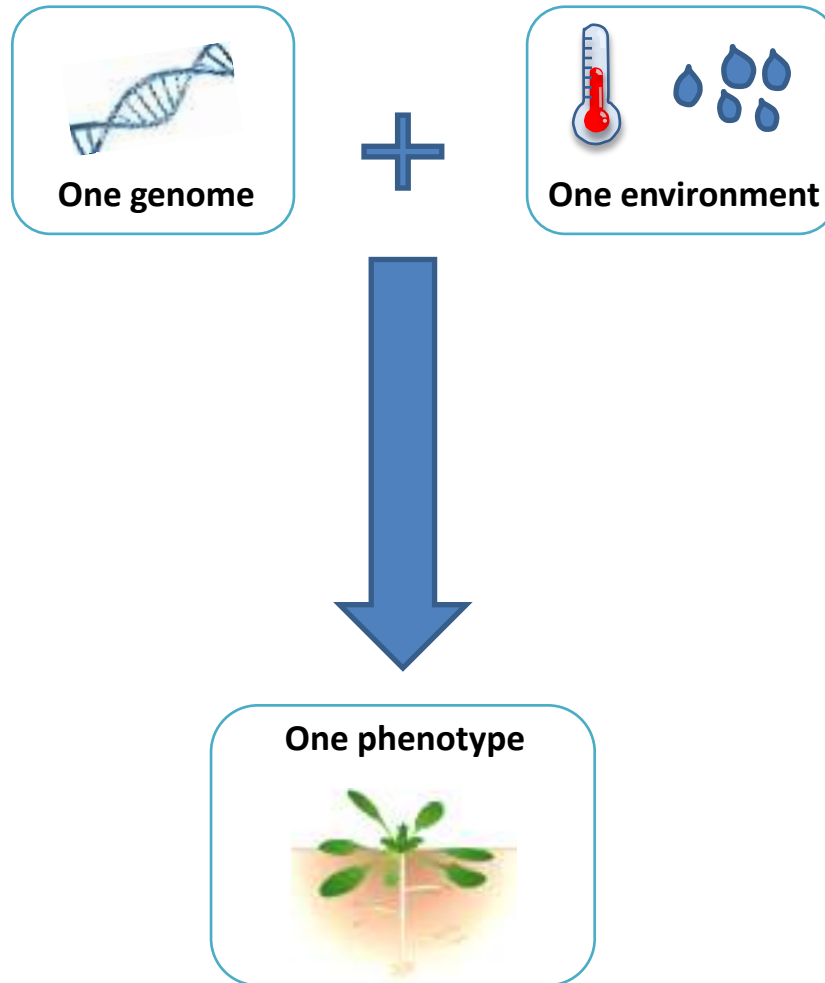


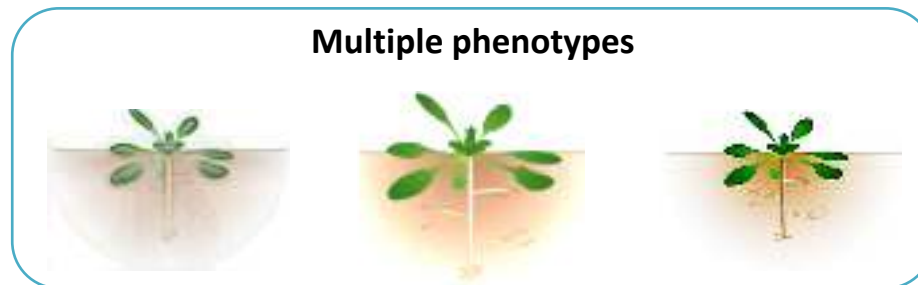
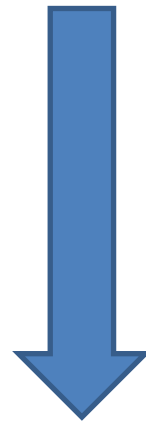
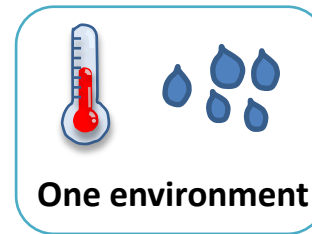
**The same, yet different –
Variability between genetically
identical plants**

Sandra Cortijo
Antoine Martin's group, BPMP (Montpellier)

Netbio– 20/09/2020



Phenotypic variability between genetically identical plants



What is transcriptional and phenotypic variability?

-> Differences between **genetically identical plants** that are in **the same environment**

NOT THE SAME AS:

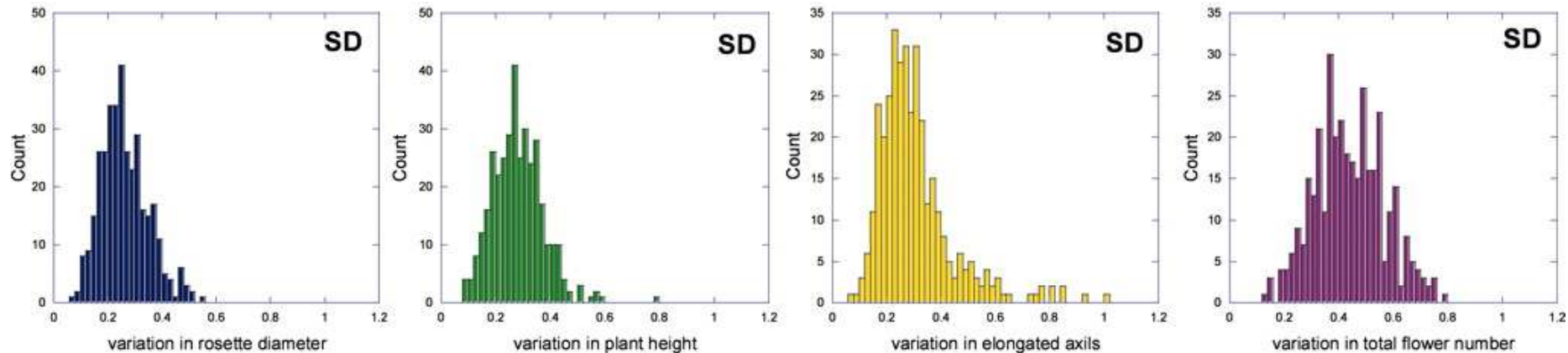
Plasticity = Response to environmental changes

Genetic variation = Differences between ecotypes or in a mutant

Phenotypic variability between genetically identical plants

Genetics of microenvironmental canalization in *Arabidopsis thaliana*

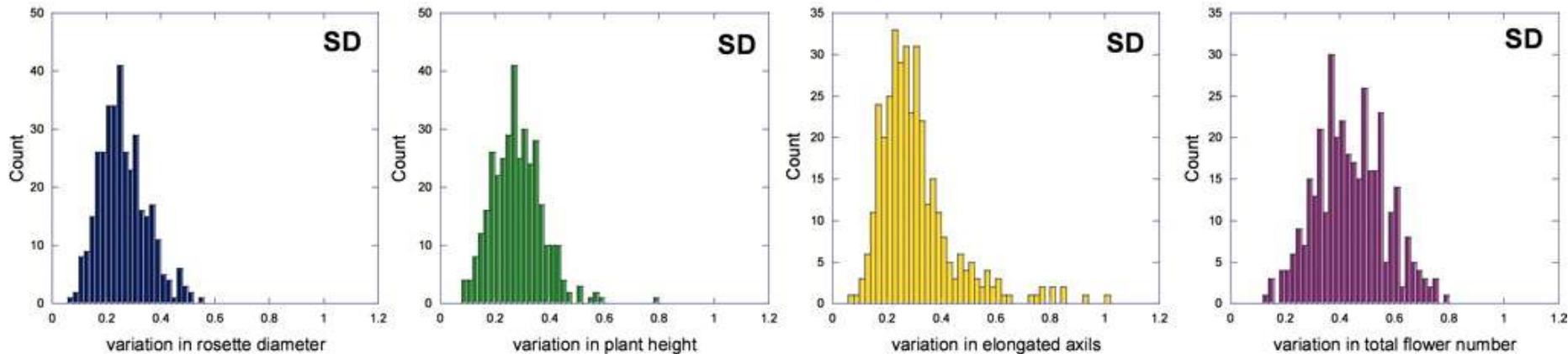
Megan C. Hall, Ian Dworkin, Mark C. Ungerer, and Michael Purugganan



Phenotypic variability between genetically identical plants

Genetics of microenvironmental canalization in *Arabidopsis thaliana*

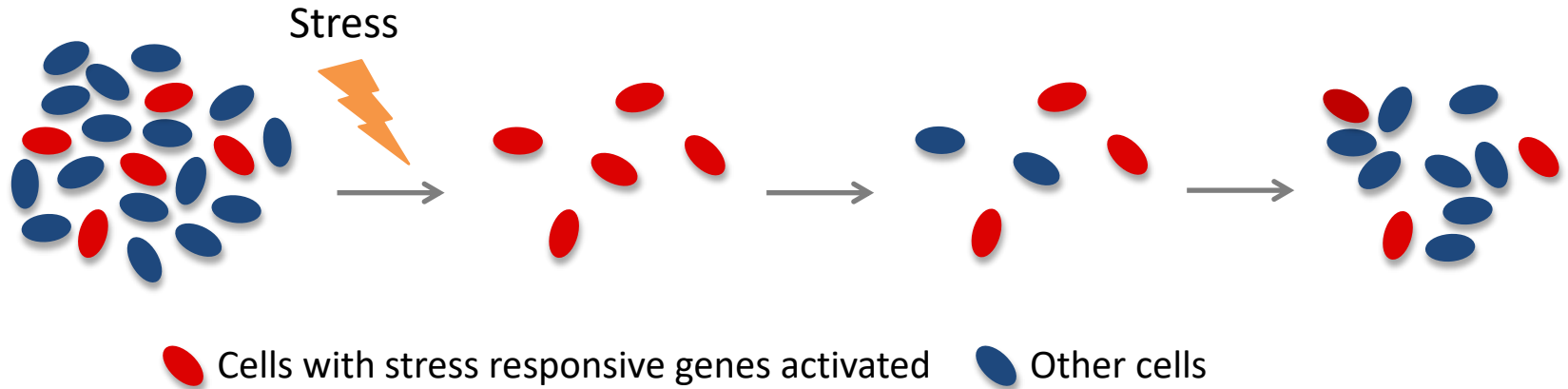
Megan C. Hall, Ian Dworkin, Mark C. Ungerer, and Michael Purugganan



+ successful GWAS and QTL studies :
shows **phenotypic variability is at least partly genetically controlled**

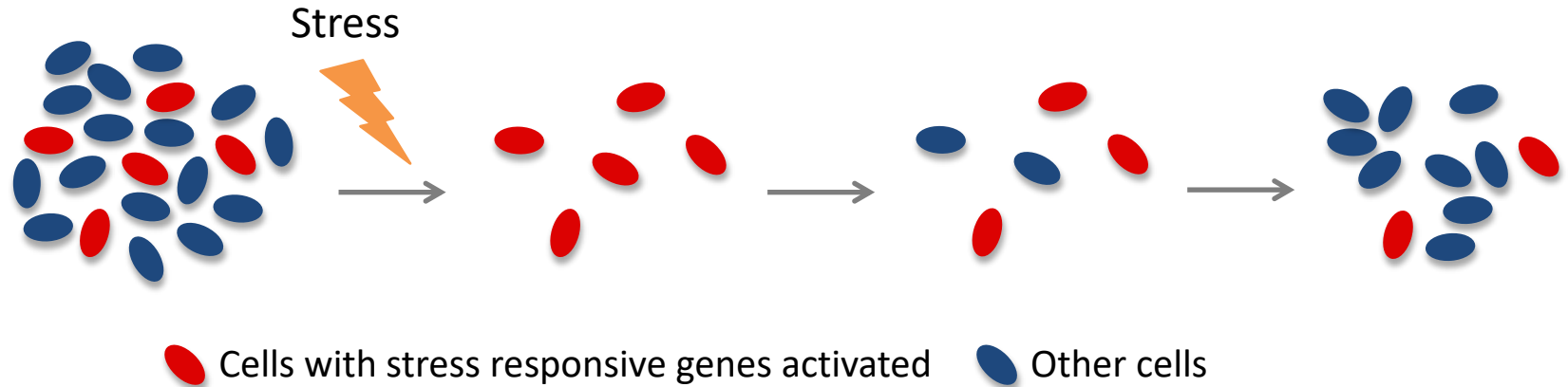
Variability between genetically identical plants could allow survival to unpredictable stress

In unicellular organisms:

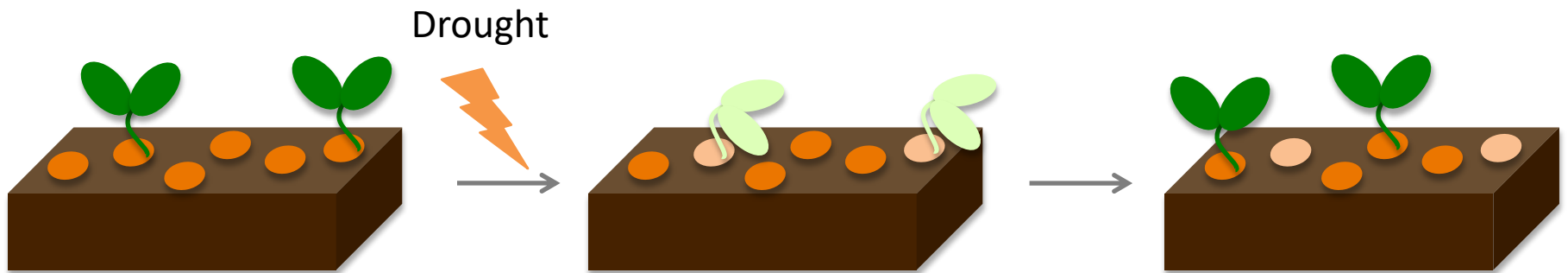


Variability between genetically identical plants could allow survival to unpredictable stress

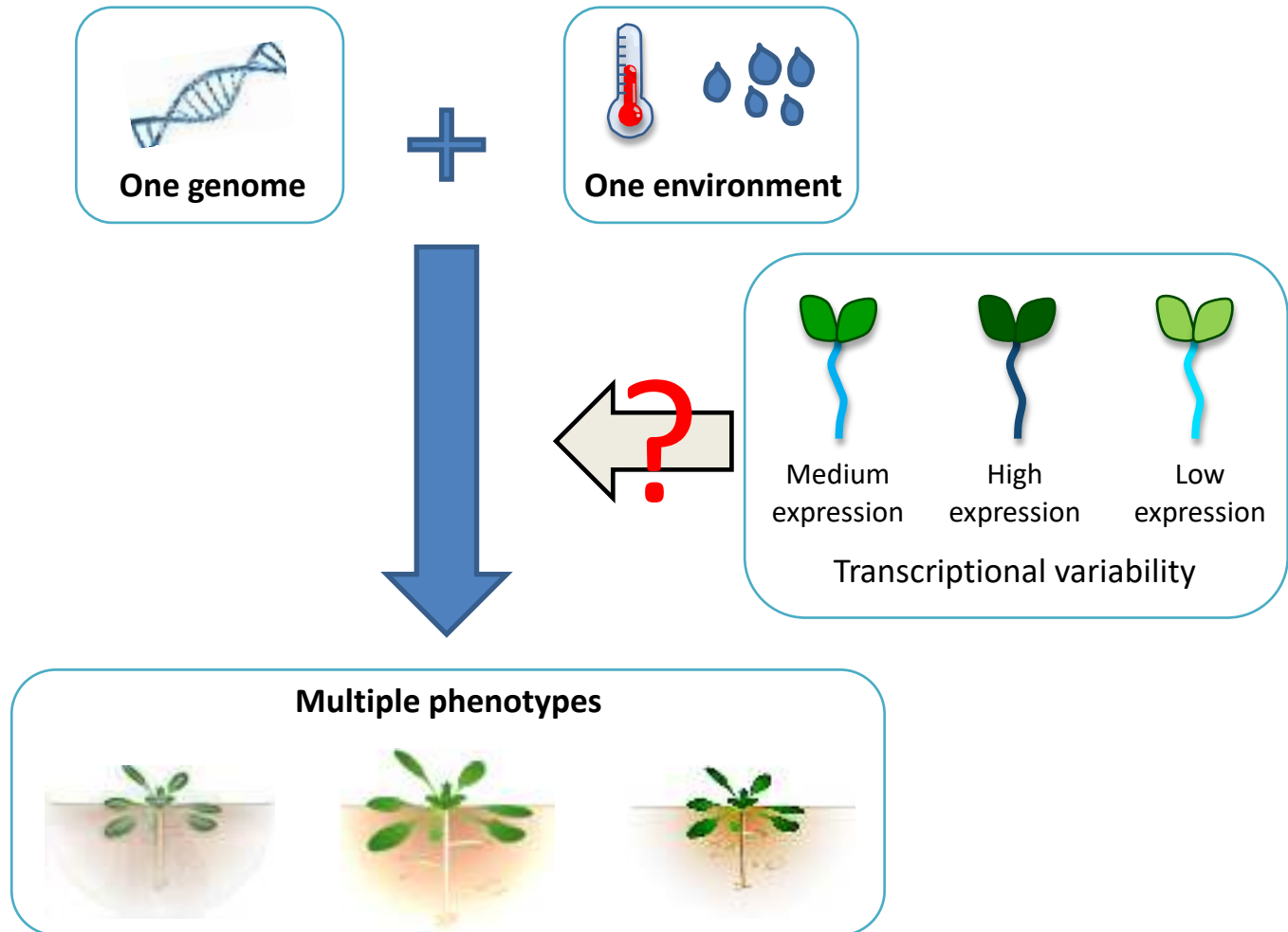
In unicellular organisms:



In plants:



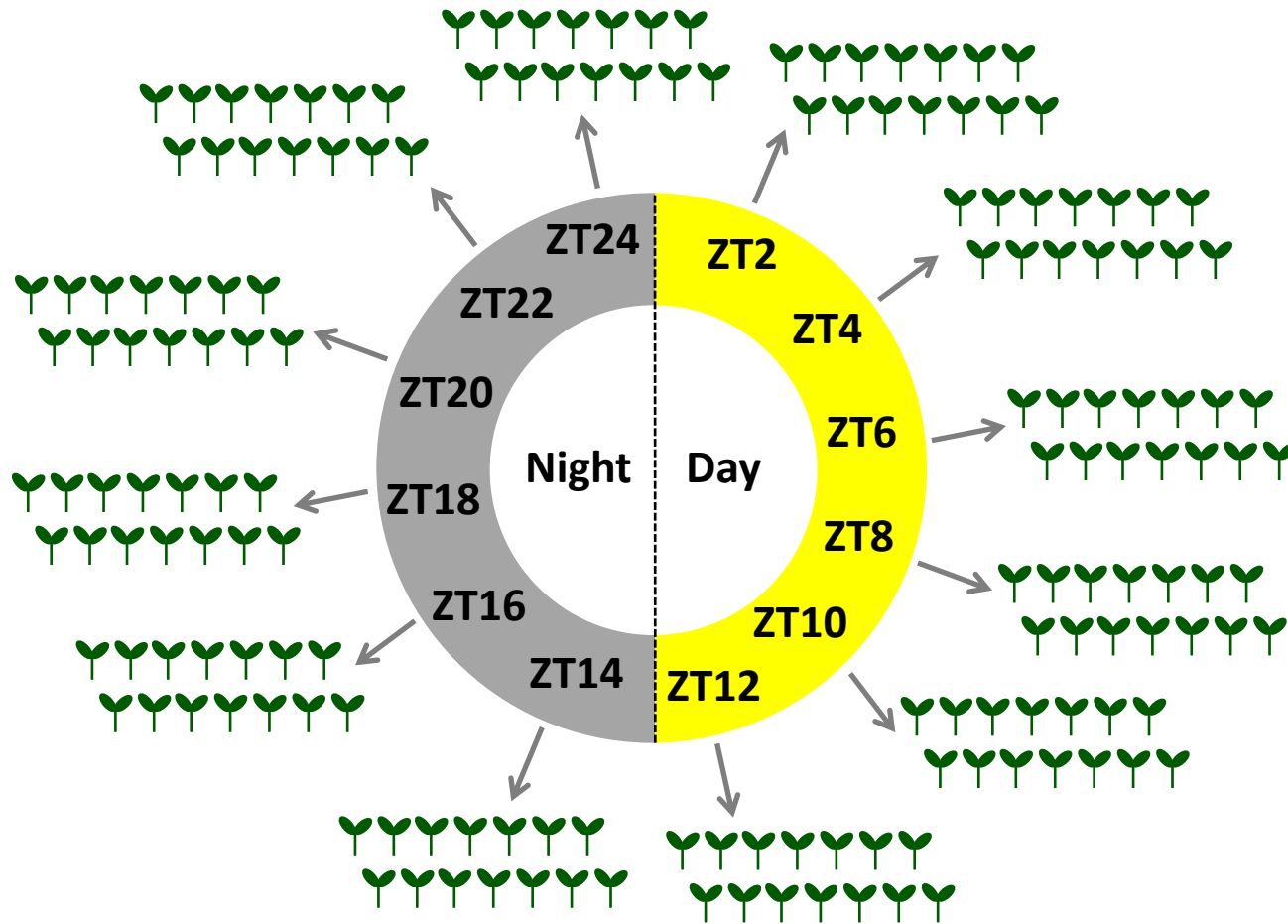
Phenotypic variability between genetically identical plants



Can we identify transcriptional variability between plants?

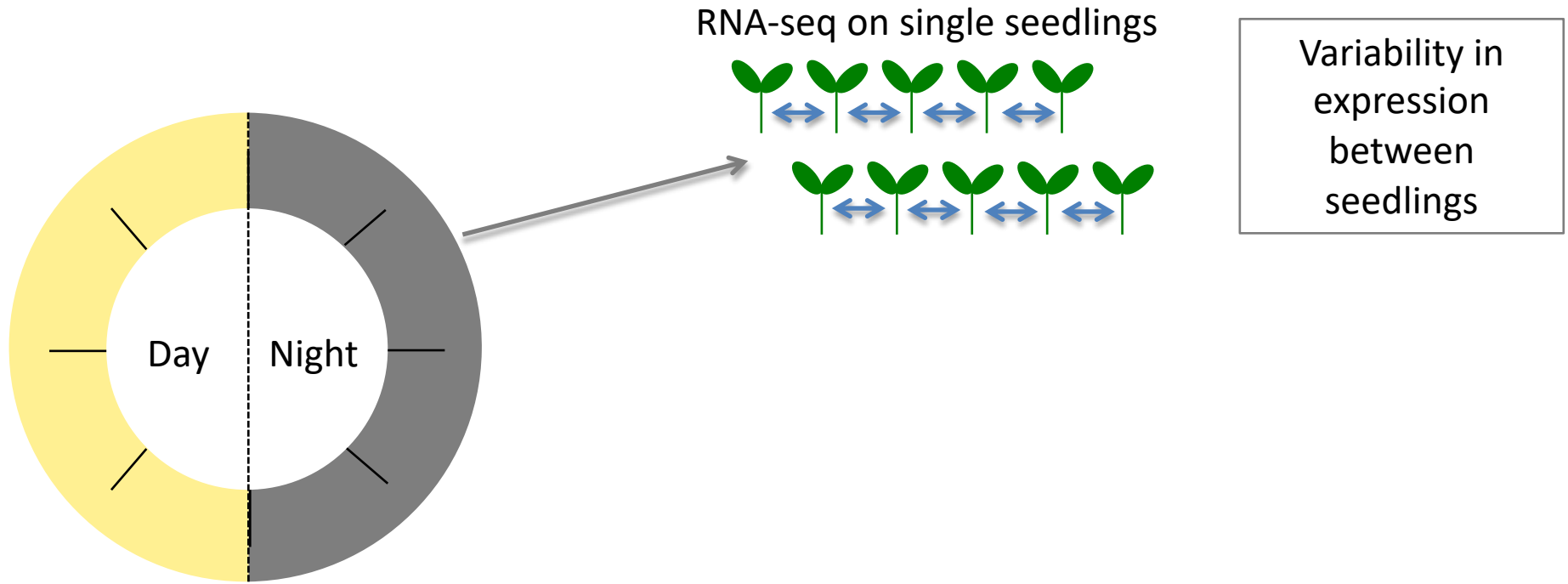
Is variability of gene expression changing during a day/night cycle?

Transcriptional variability during a 24hrs cycle

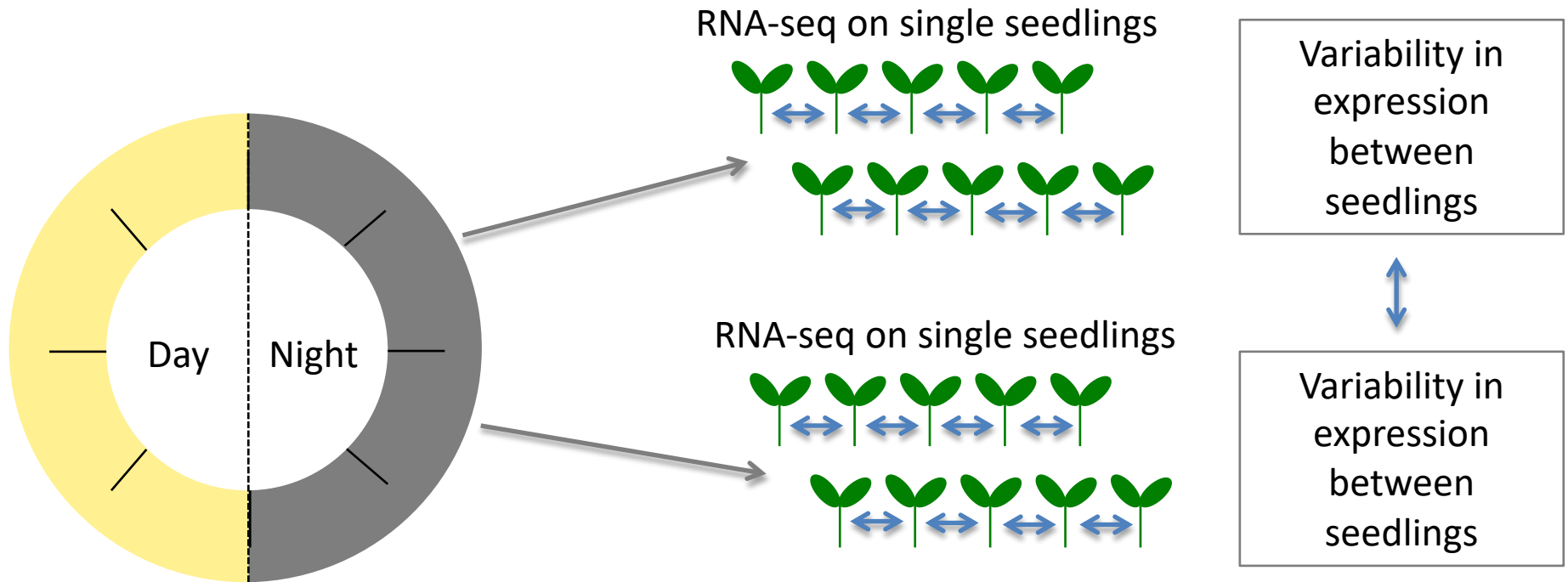


RNA-seq on single seedlings
(14 seedlings per time point)

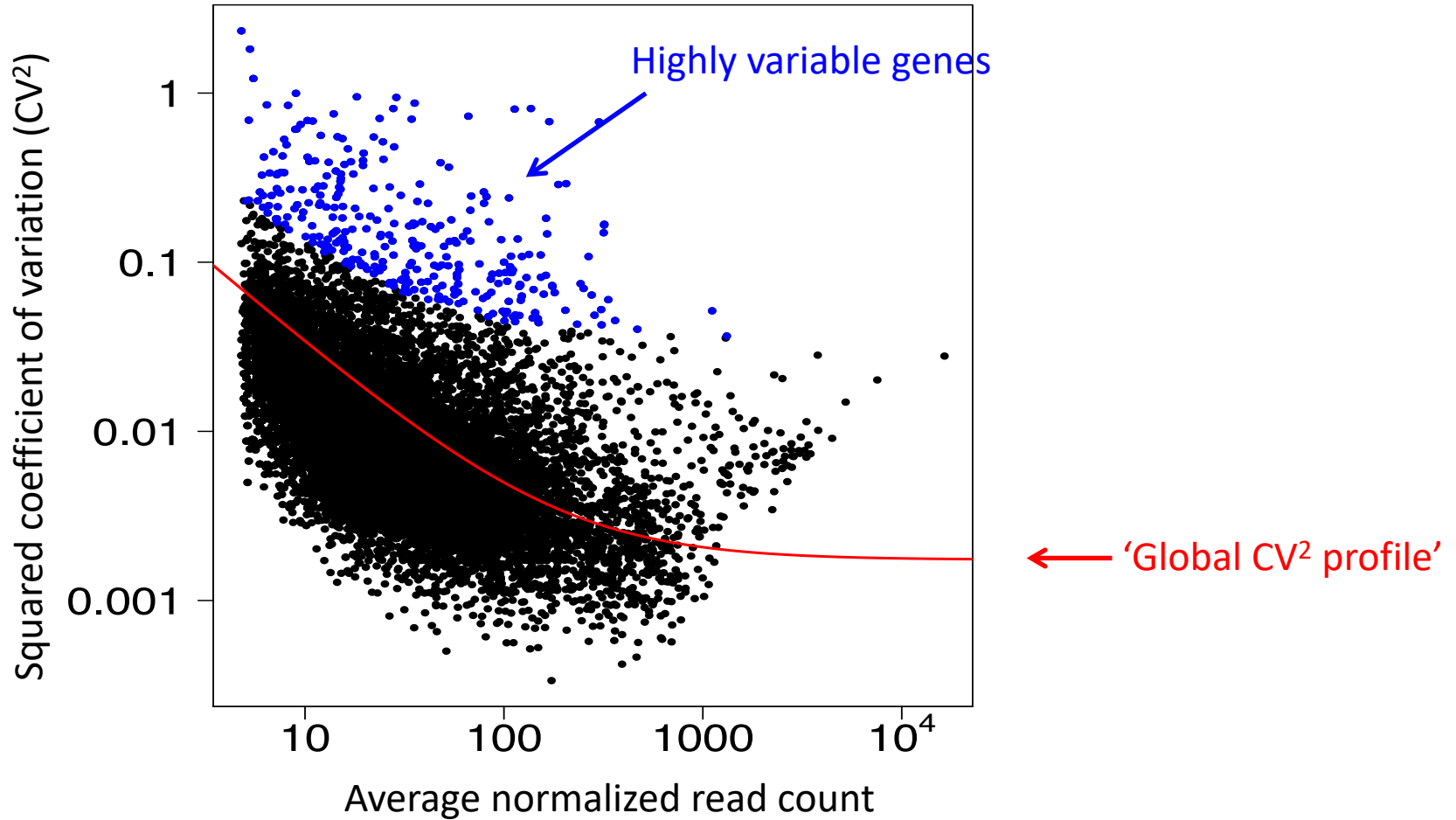
Transcriptional variability during a 24hrs cycle



Transcriptional variability during a 24hrs cycle

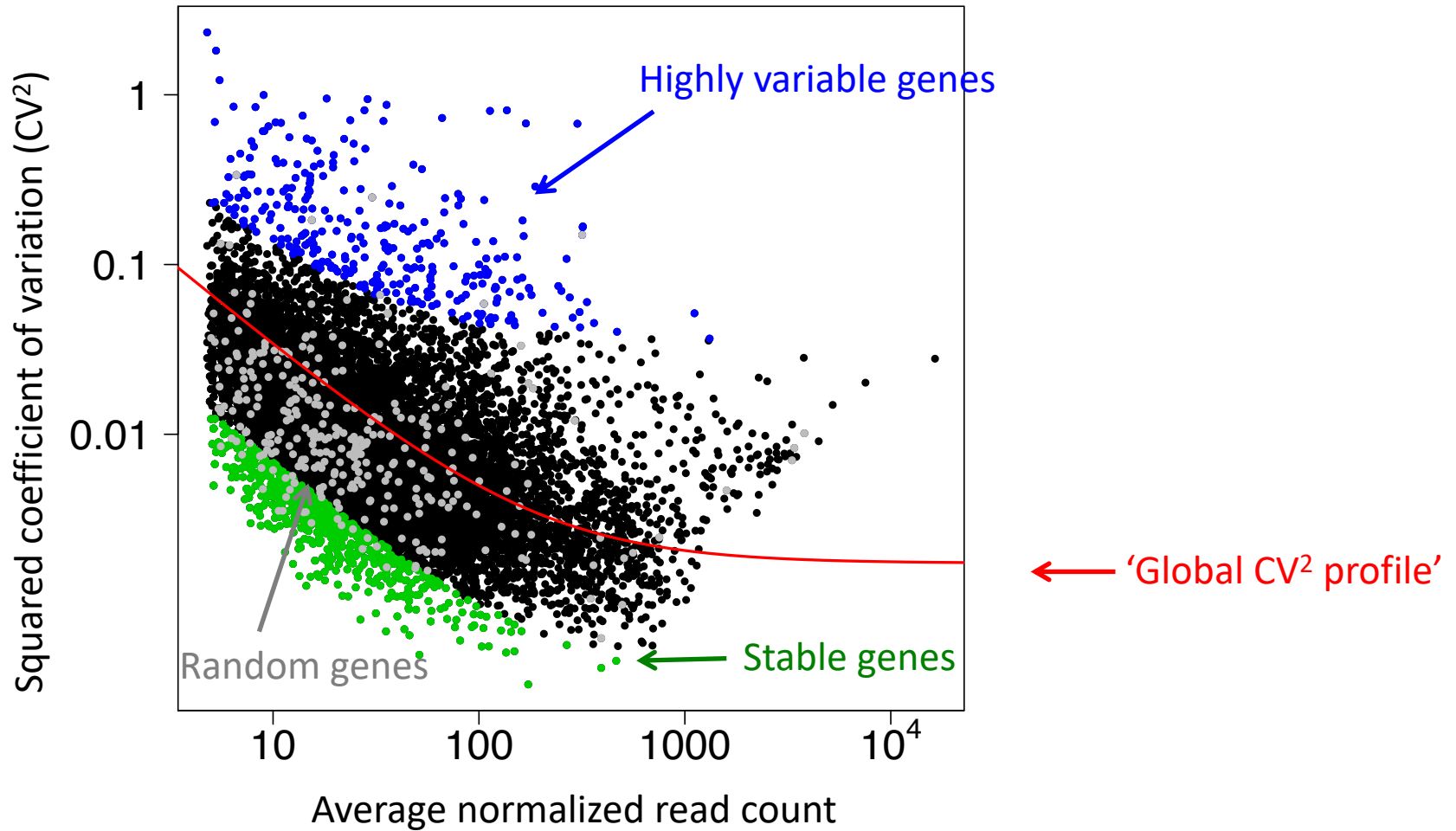


How to measure transcriptional variability?



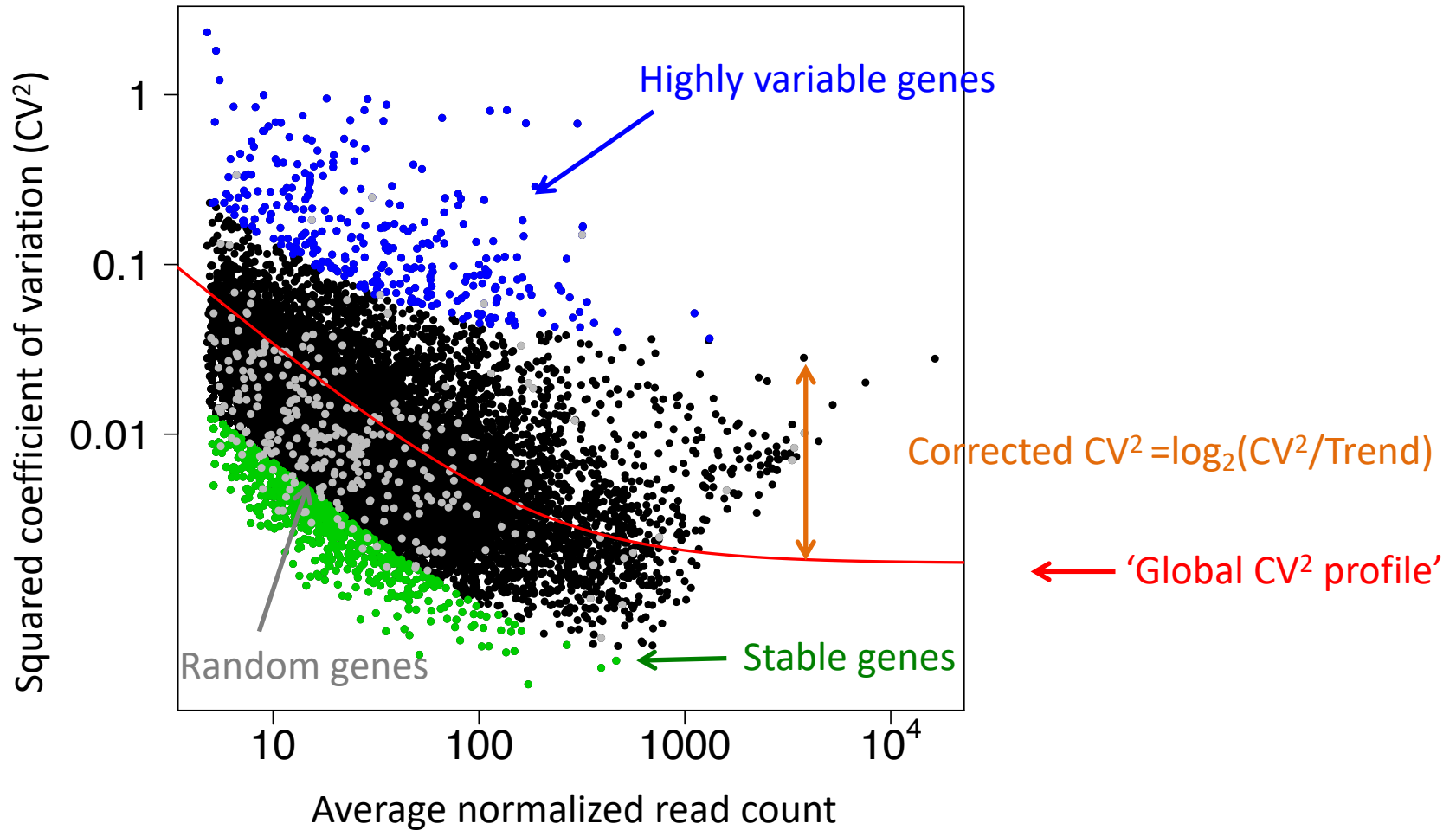
$$CV^2 = \text{variance}/(\text{average}^2)$$

How to measure transcriptional variability?



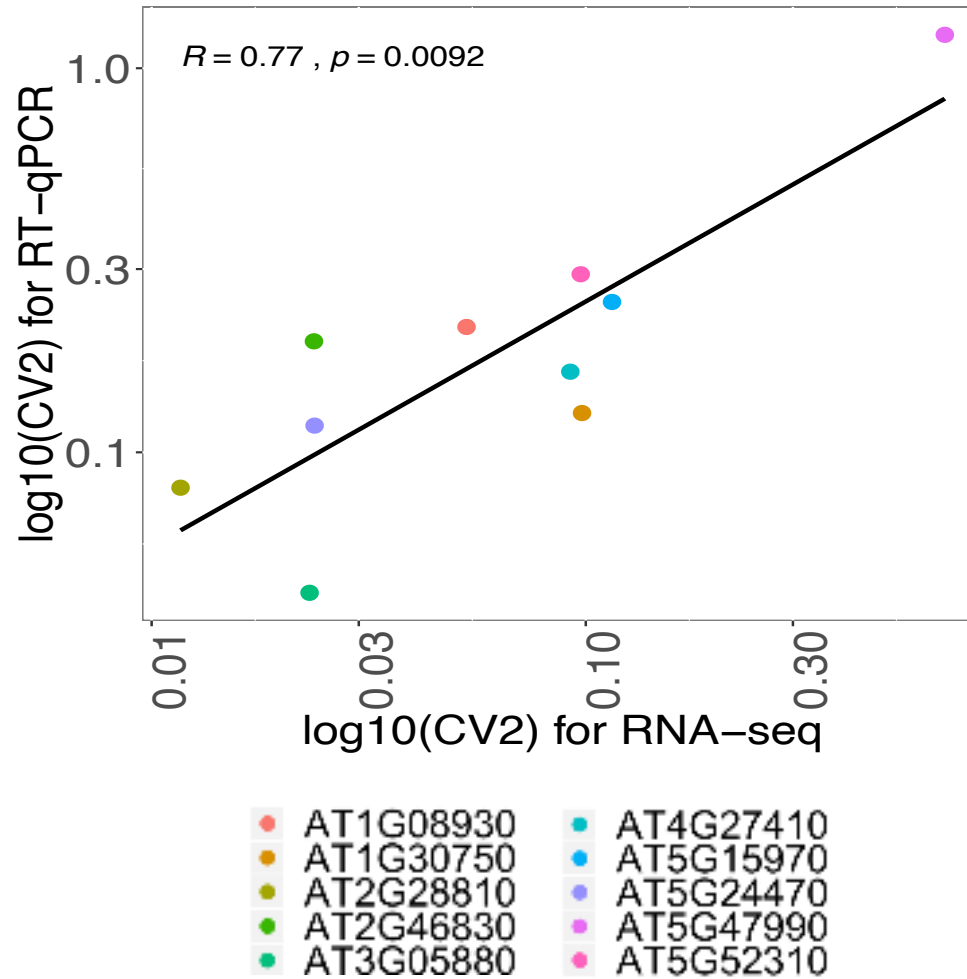
$$CV^2 = \text{variance} / (\text{average}^2)$$

How to measure transcriptional variability?



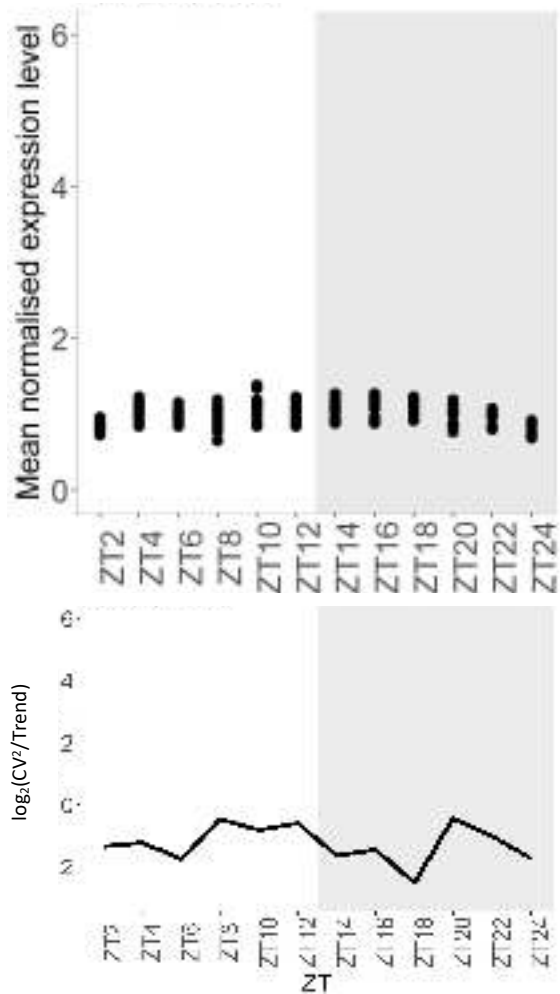
$$CV^2 = \text{variance}/(\text{average}^2)$$

Confirming the results by RT-qPCR



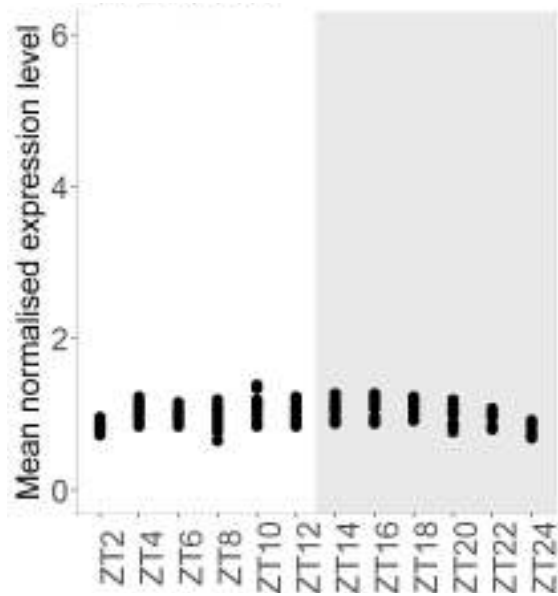
Variability profiles during the time course

AT2G28810 (not HVG)

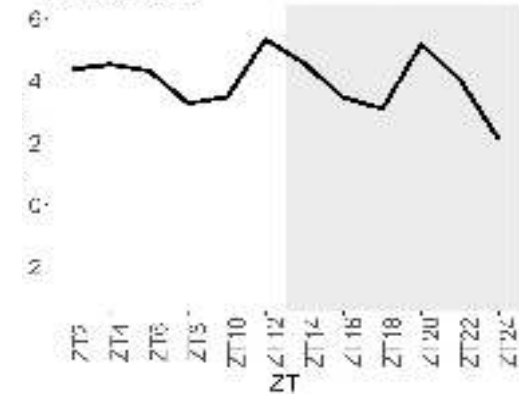
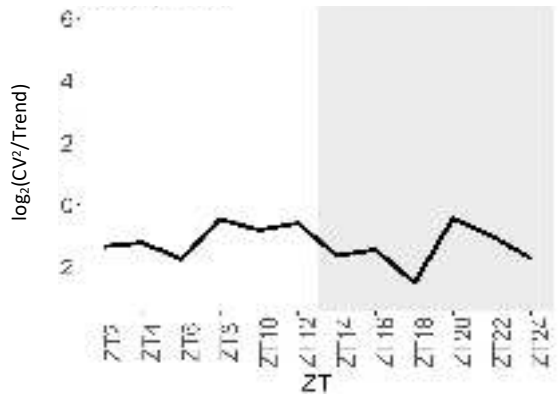
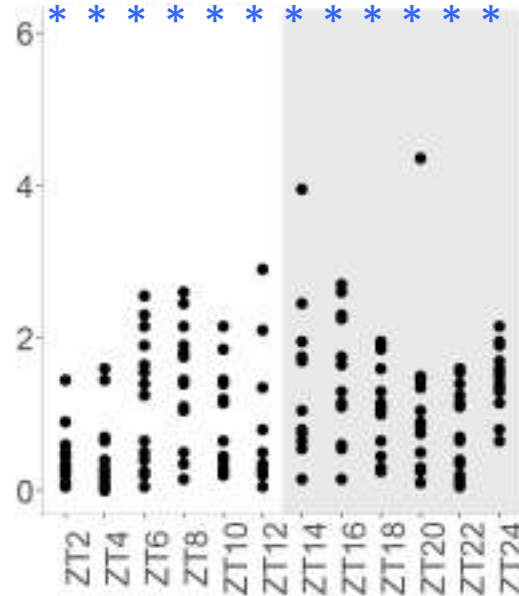


Variability profiles during the time course

AT2G28810 (not HVG)

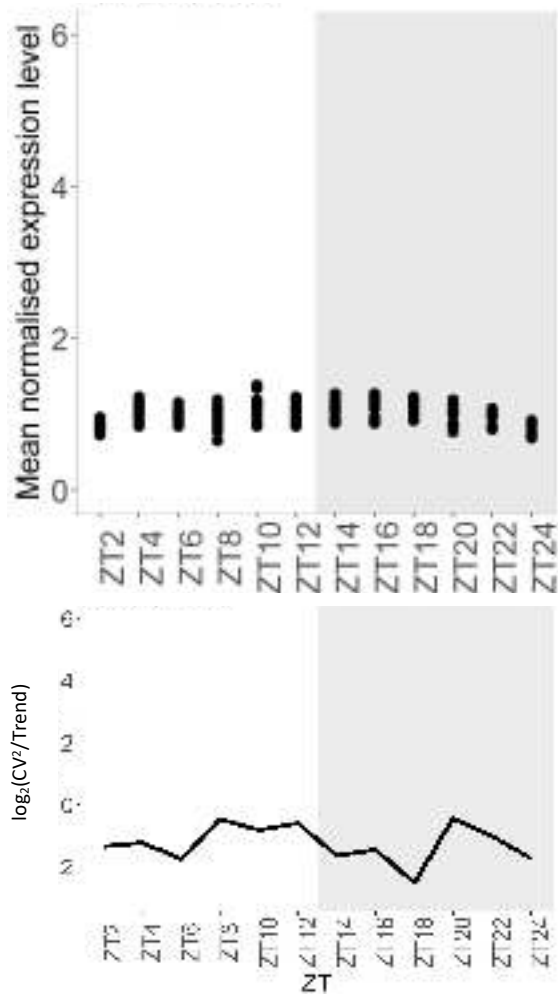


AT5G47990 (HVG)

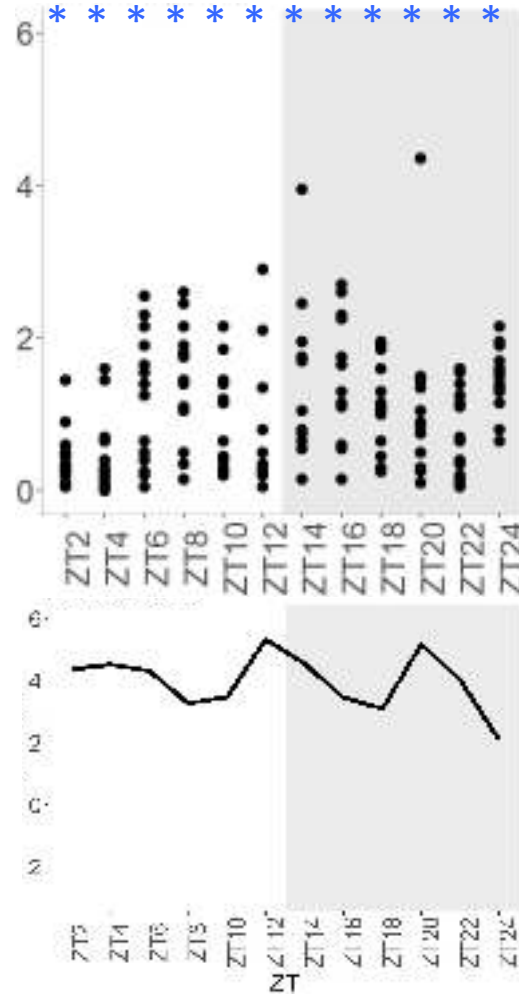


Variability profiles during the time course

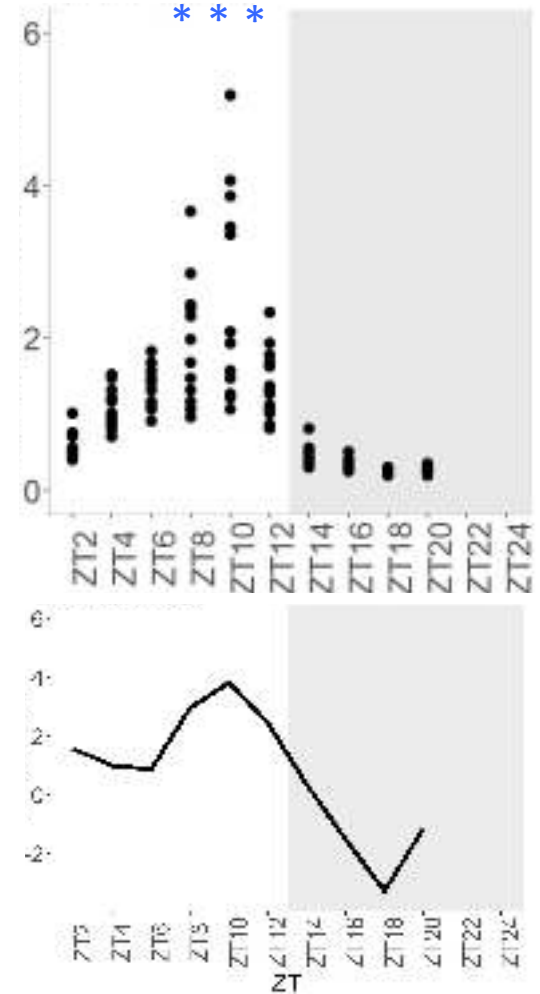
AT2G28810 (not HVG)



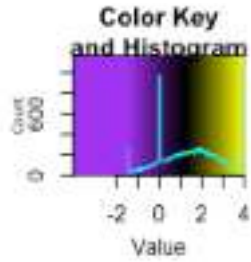
AT5G47990 (HVG)



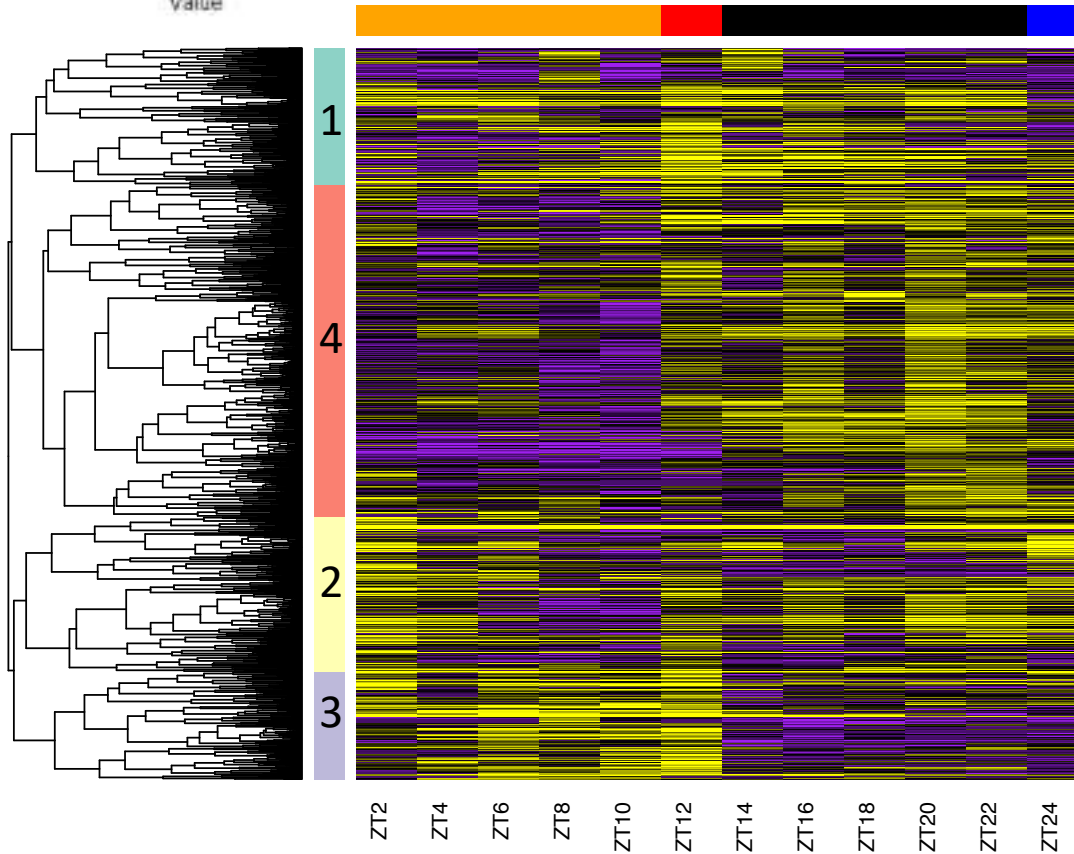
AT5G52310 (HVG at ZT8, ZT10, ZT12)



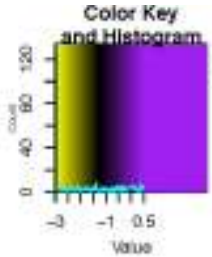
Variability profiles during the time course



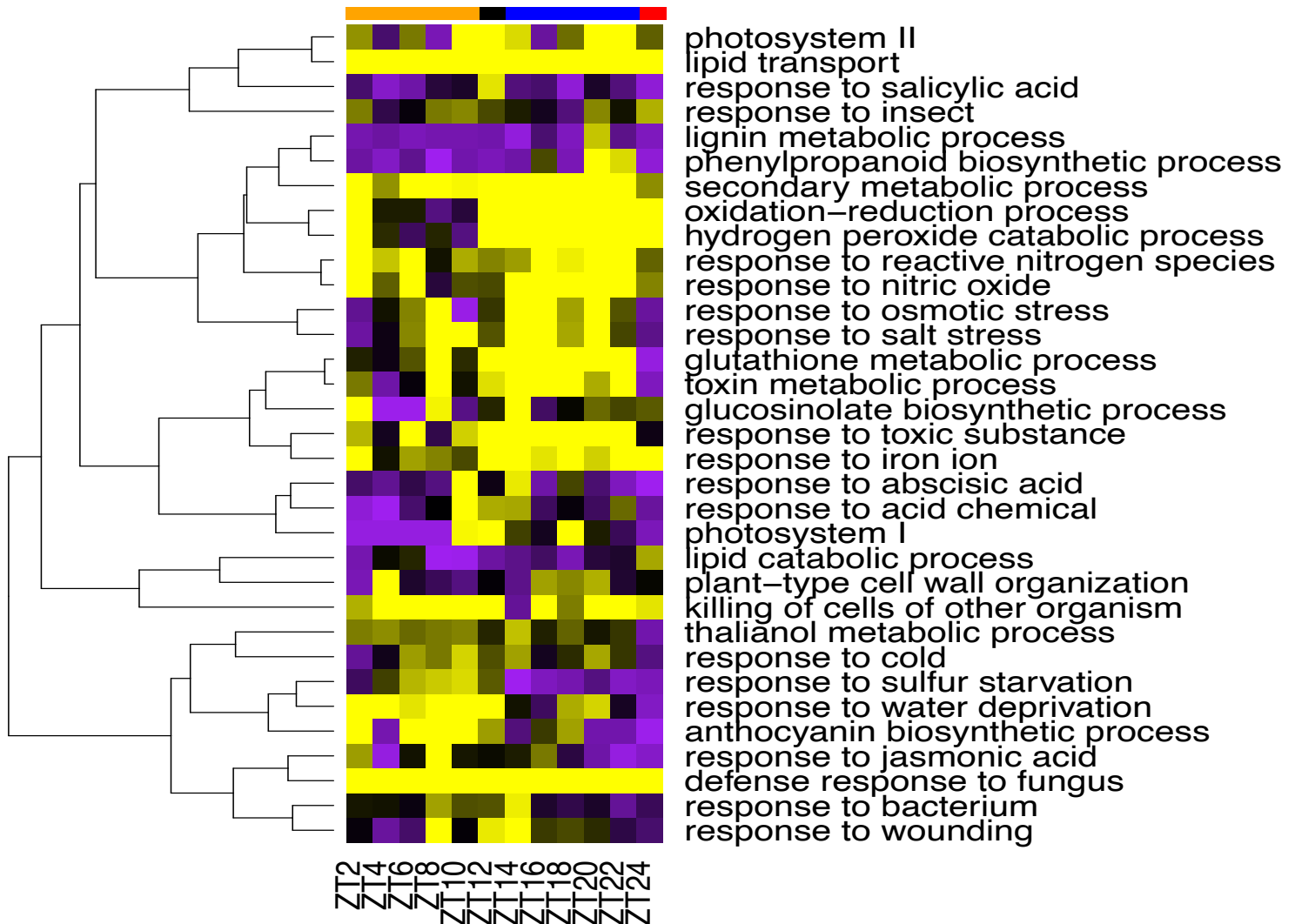
$\text{Log}_2(\text{CV}^2/\text{trend})$, HVG

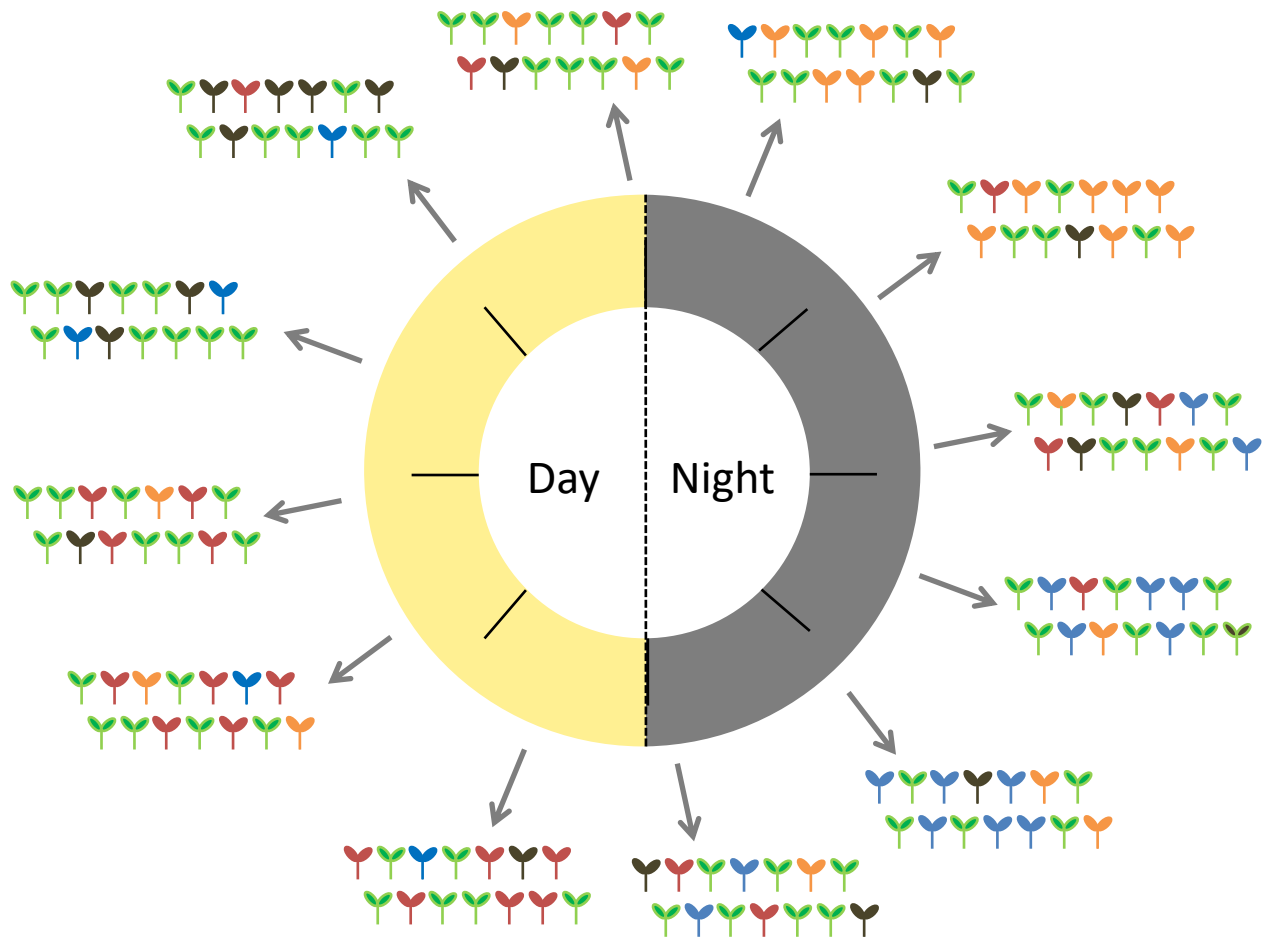


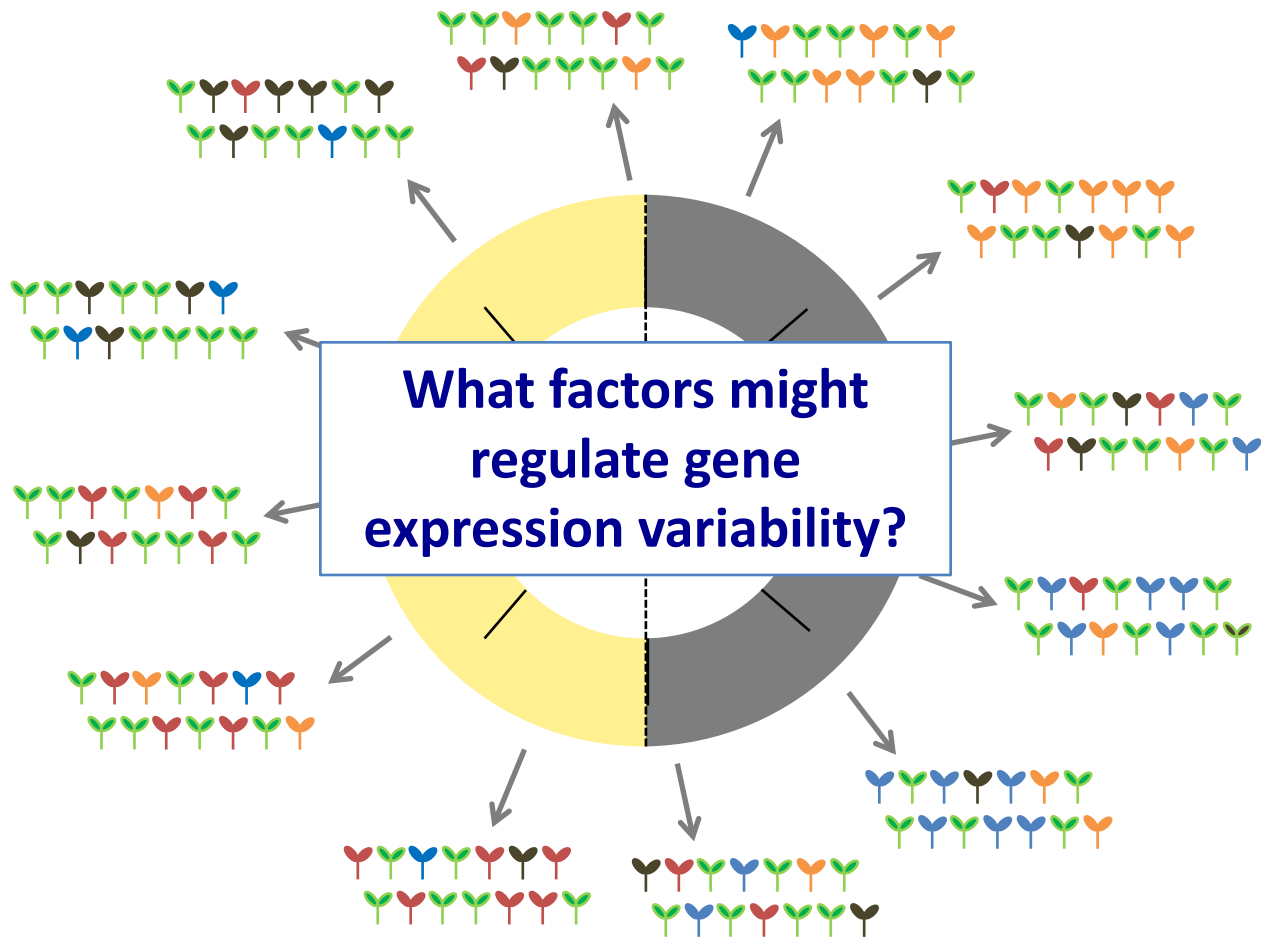
HVGs are enriched for environmentally responsive genes



HVG, $\text{Log}_{10}(\text{FDR})$ of GO

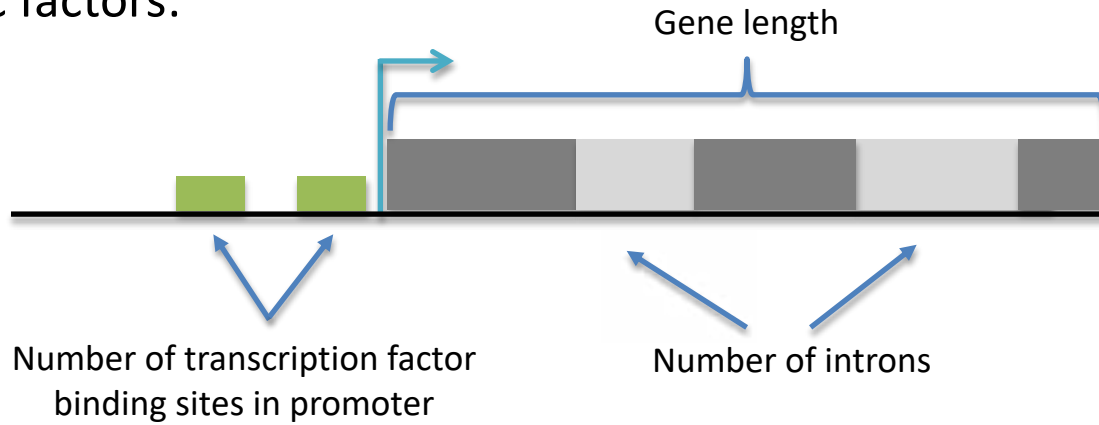






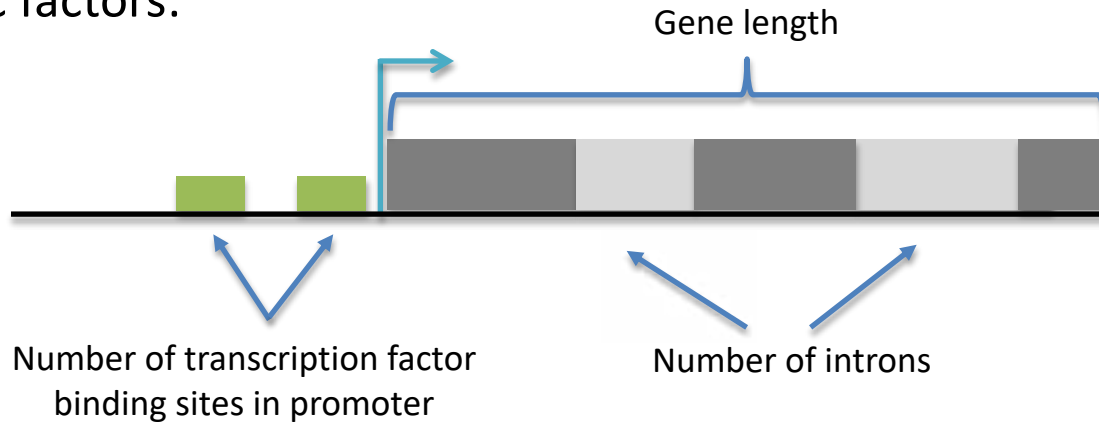
Genomic and epigenomic factors we analysed

- Genomic factors:

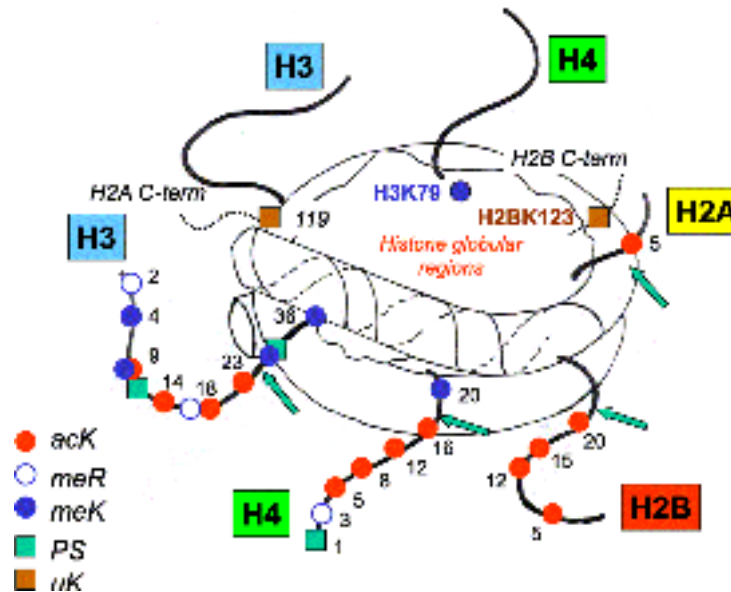


Genomic and epigenomic factors we analysed

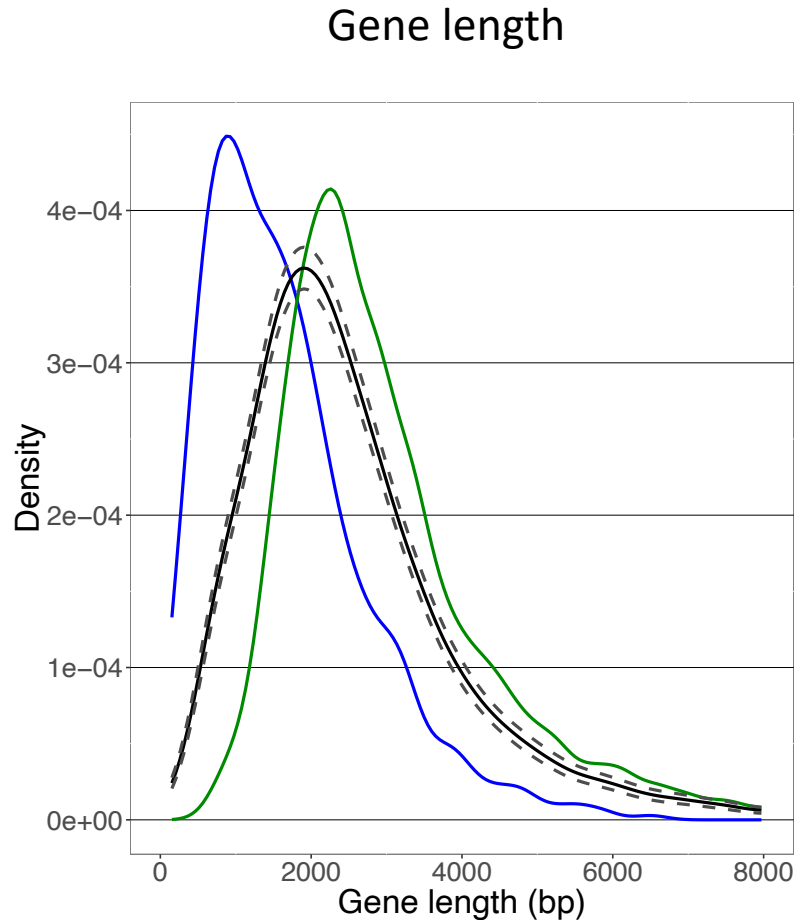
- Genomic factors:



- Epigenomic factors:



HVGs tend to be smaller and targeted with more TFs



— HVG

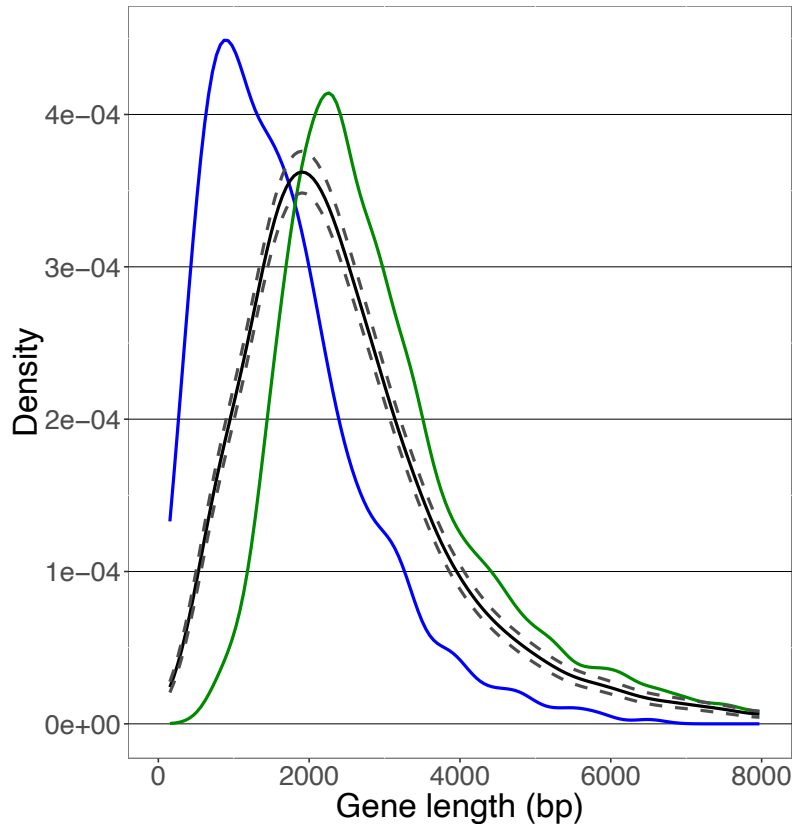
— LVG

— Average of 1000 random sets

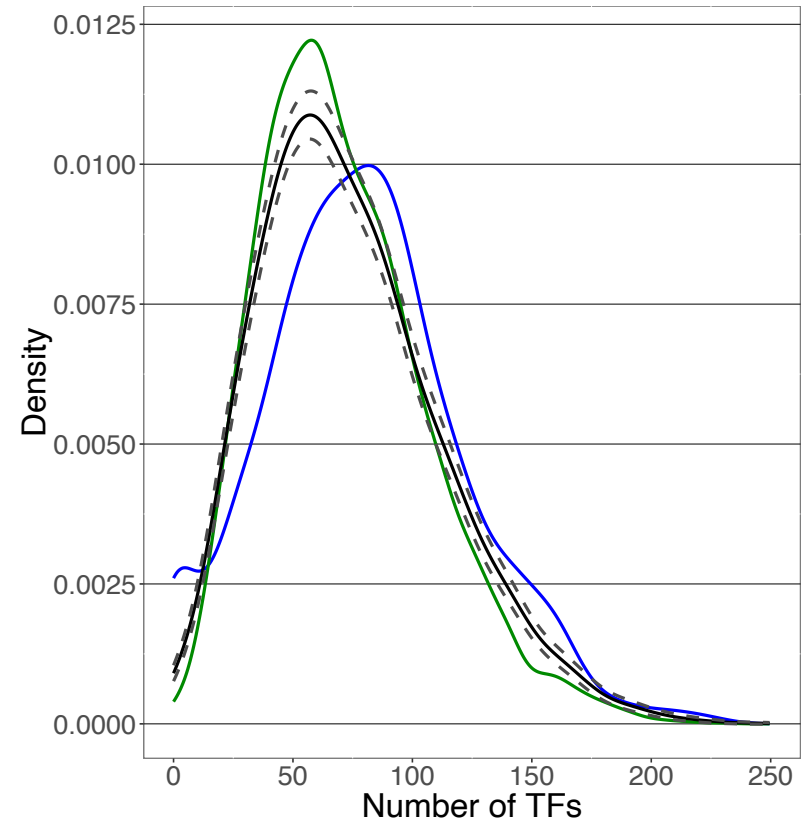
- - - 95% confidence interval of 1000 random sets

HVGs tend to be smaller and targeted with more TFs

Gene length

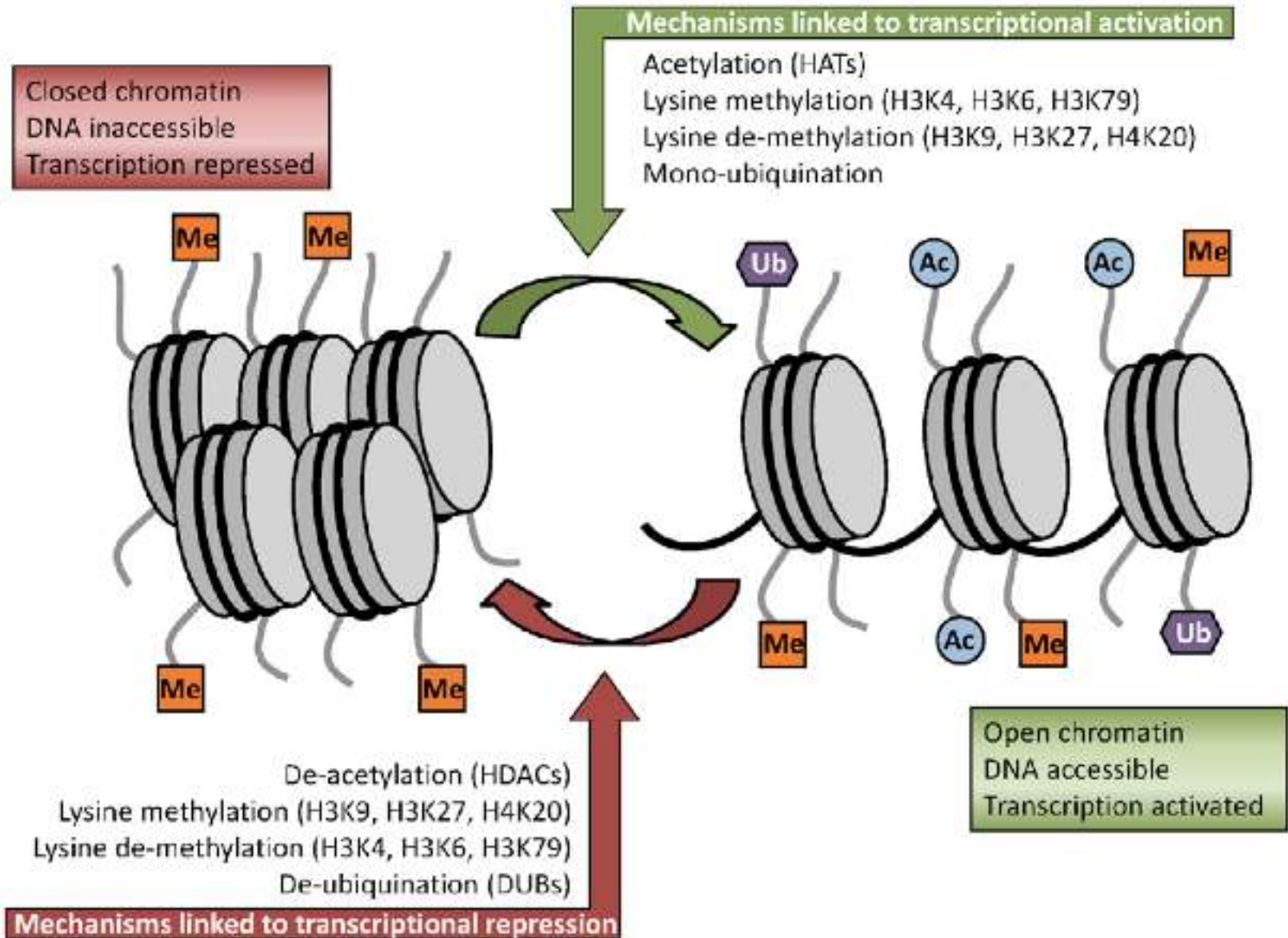


Number of TFs binding to the promoter of the gene

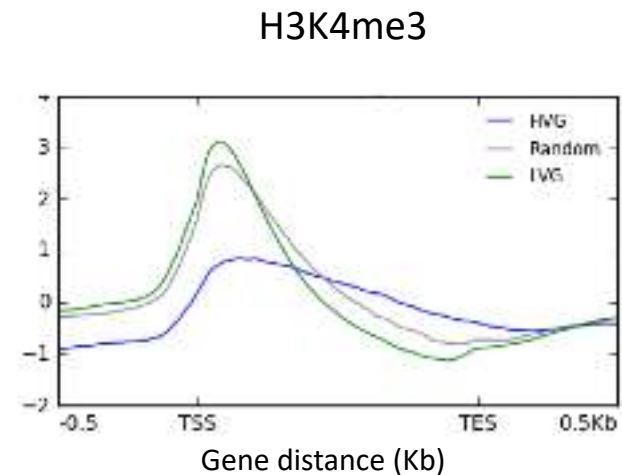
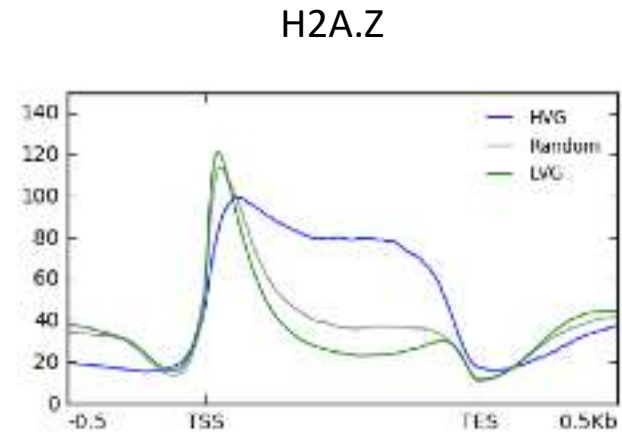
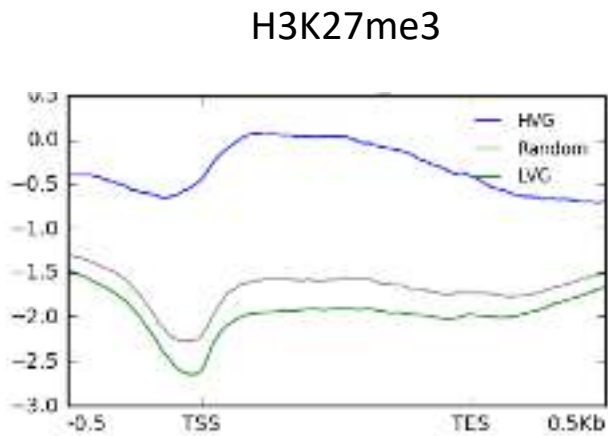


- HVG
- LVG
- Average of 1000 random sets
- - - 95% confidence interval of 1000 random sets

Chromatin environment of HVGs



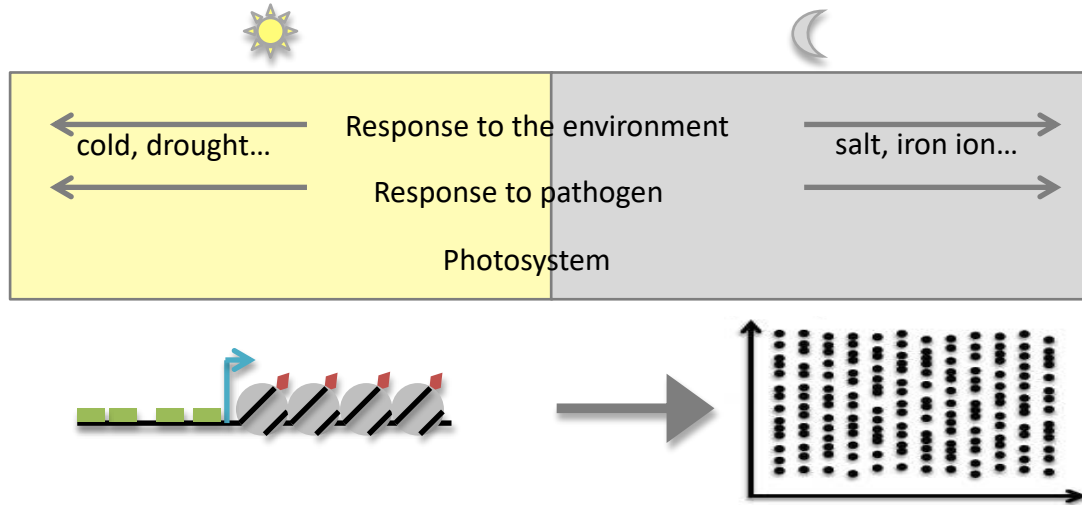
HVGs tend to be characterized by a 'closed' chromatin environment



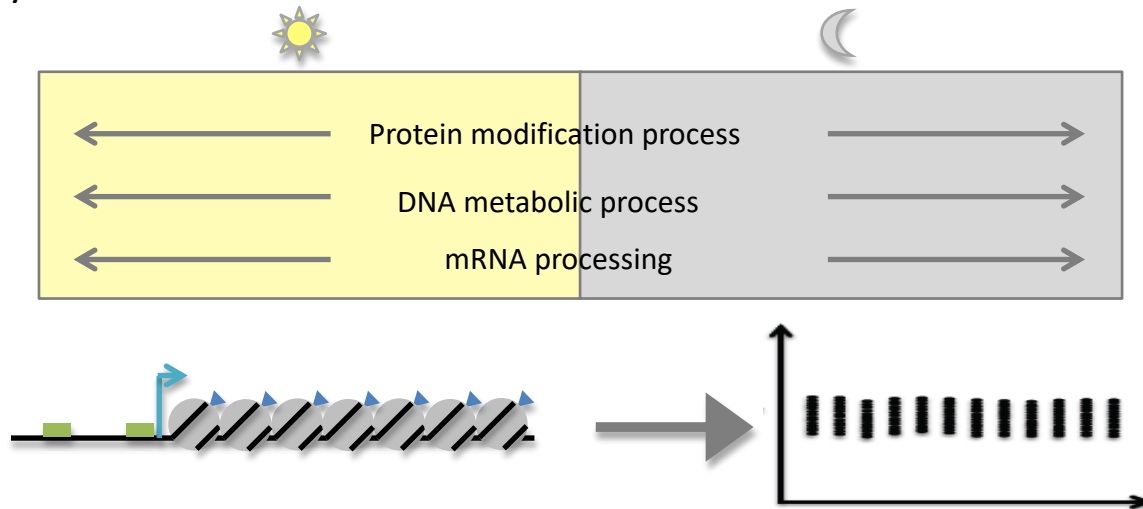
■ variable ■ stable ■ random

Summary

Highly Variable Genes



Lowly Variable Genes



■ TF binding motif

● 'closed' chromatin

● 'open' chromatin

AraNoisy, a webApp to explore gene expression variability for your gene of interest:
<https://jlggroup.shinyapps.io/AraNoisy/>

Secure | <https://jlggroup.shinyapps.io/AraNoisy/>

AraNoisy About [Single seedlings profiles](#)

Gene Variability Profile

Input a gene name (ex: AT5G52310) and click on the 'Draw plot' button

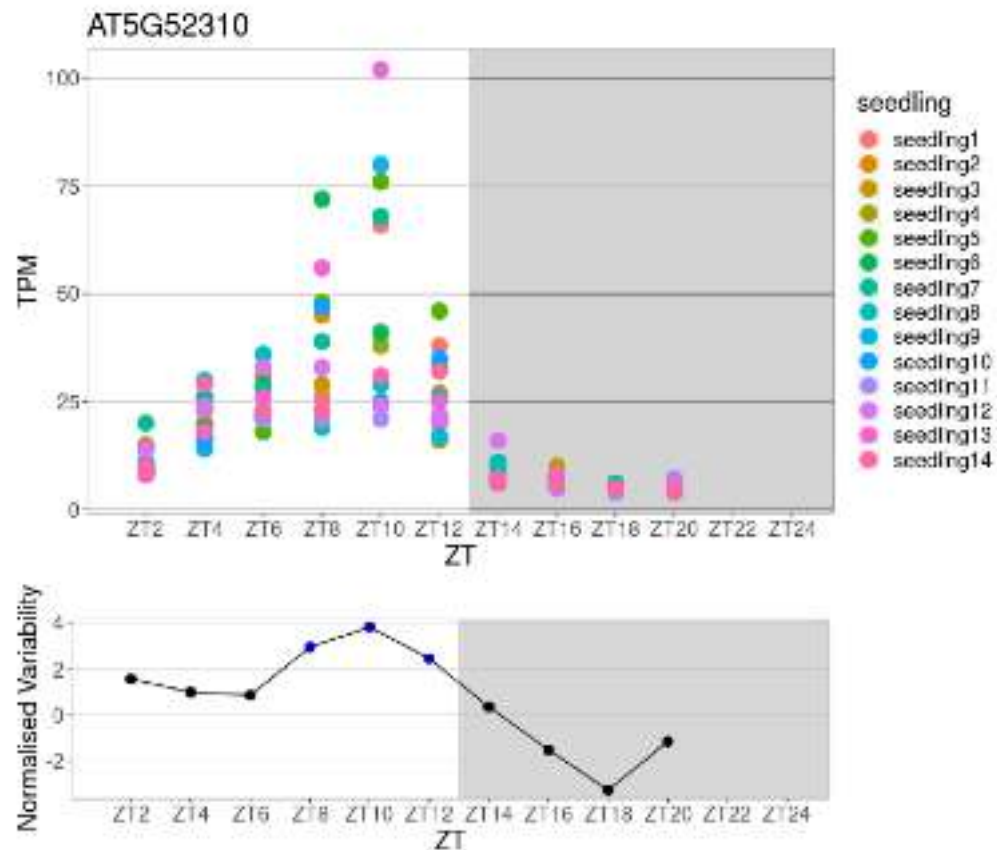
Draw plots

Download top plot

Download bottom plot

Download expression table for this gene

Download variability table for this gene





Can we harness inter-individual gene expression variability to better understand gene expression regulation?

**In collaboration with Sebastian Ahnert
(University of Cambridge, UK)**

Why Gene Co-expression Networks are useful

Help to identify genes that are co-regulated. It suggests the genes can:

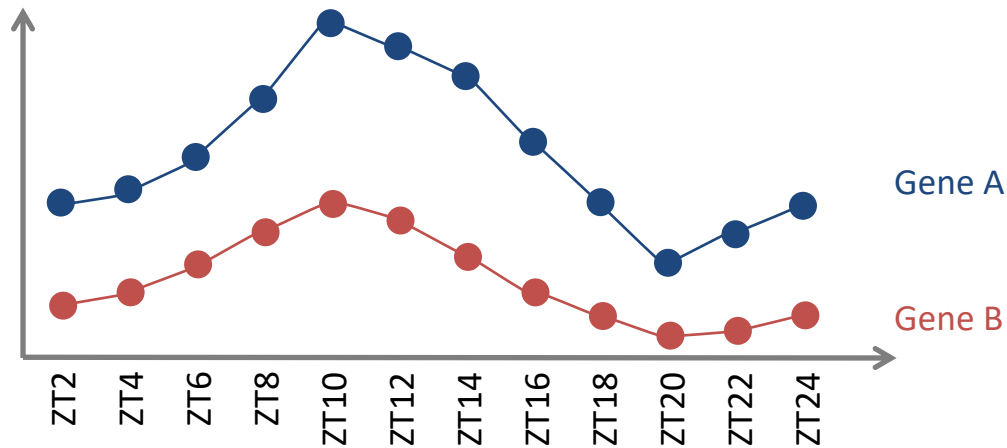
- Have a similar function
- Be involved in a common biological process
- Be controlled by the same transcriptional regulatory program

This can be used to :

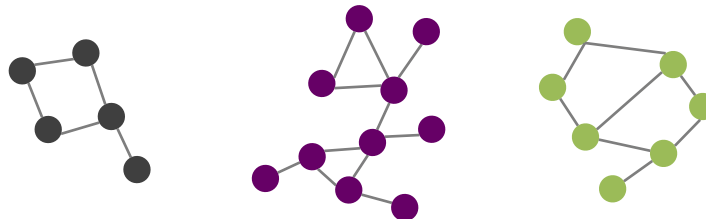
- Identify new genes in a pathway
- Identify new functions of a gene
- Identify potential regulators

What are Gene Co-expression Networks

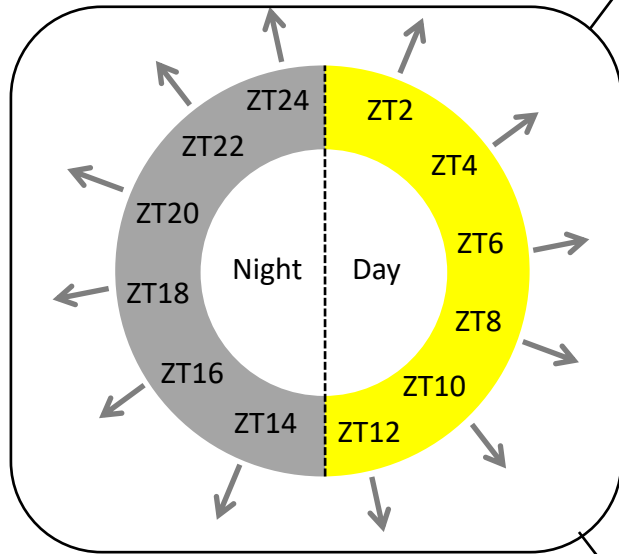
- Gene co-expression network can be constructed by looking for pairs of genes which show a similar expression pattern across samples



- Modules are cluster of genes that are more connected in the co-expression network

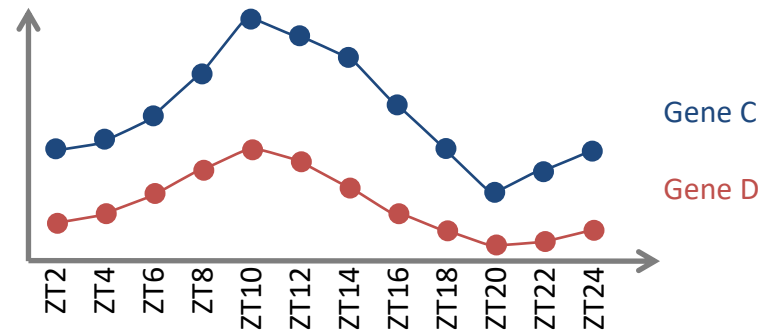


Gene Co-expression Networks: The usual approach uses perturbations

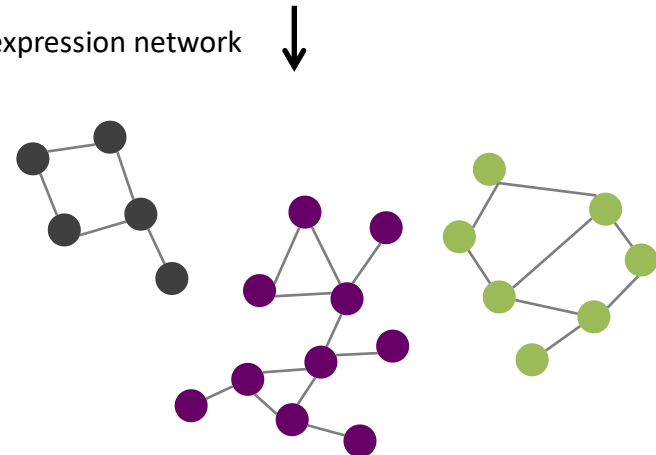


Time course co-expression network

1. Identification of co-expressed genes between time point using the average expression level of all 14 seedlings in each time point

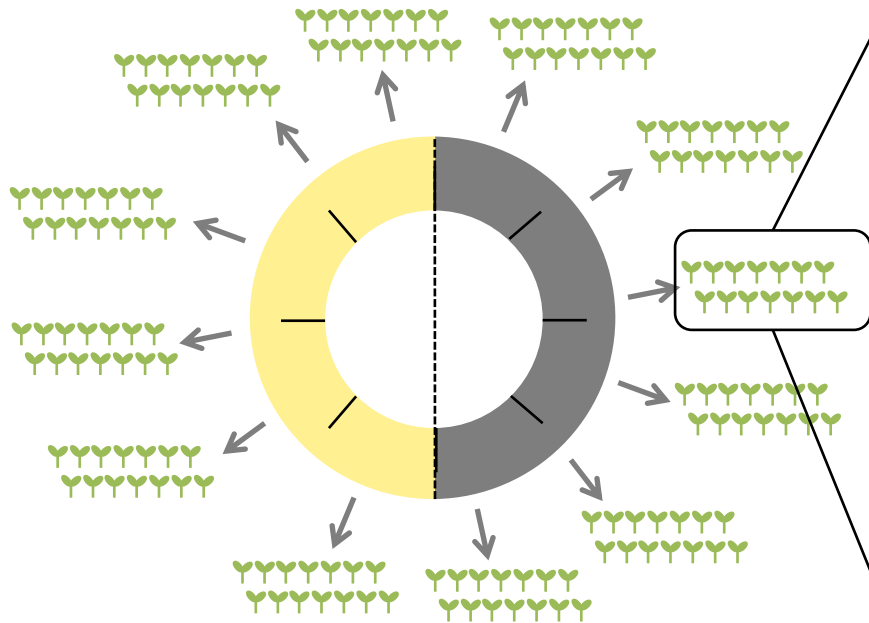


2. Co-expression network



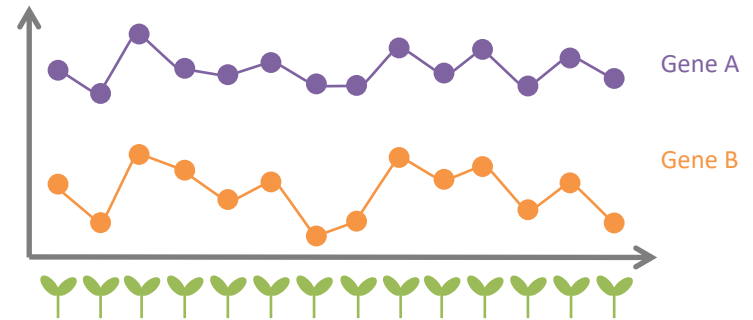
Gene Co-expression Networks

Using inter-individual gene expression variability

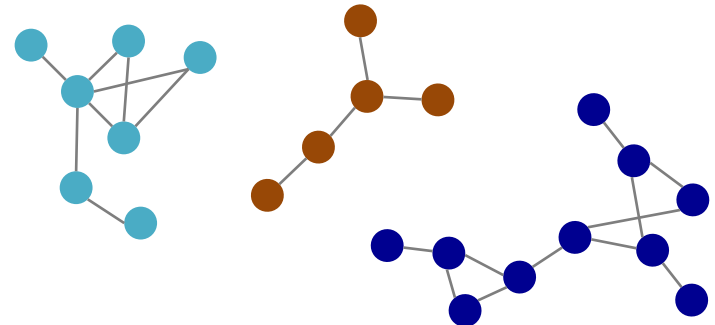


Seedlings co-expression network

1. Identification of co-expressed genes between 14 seedlings

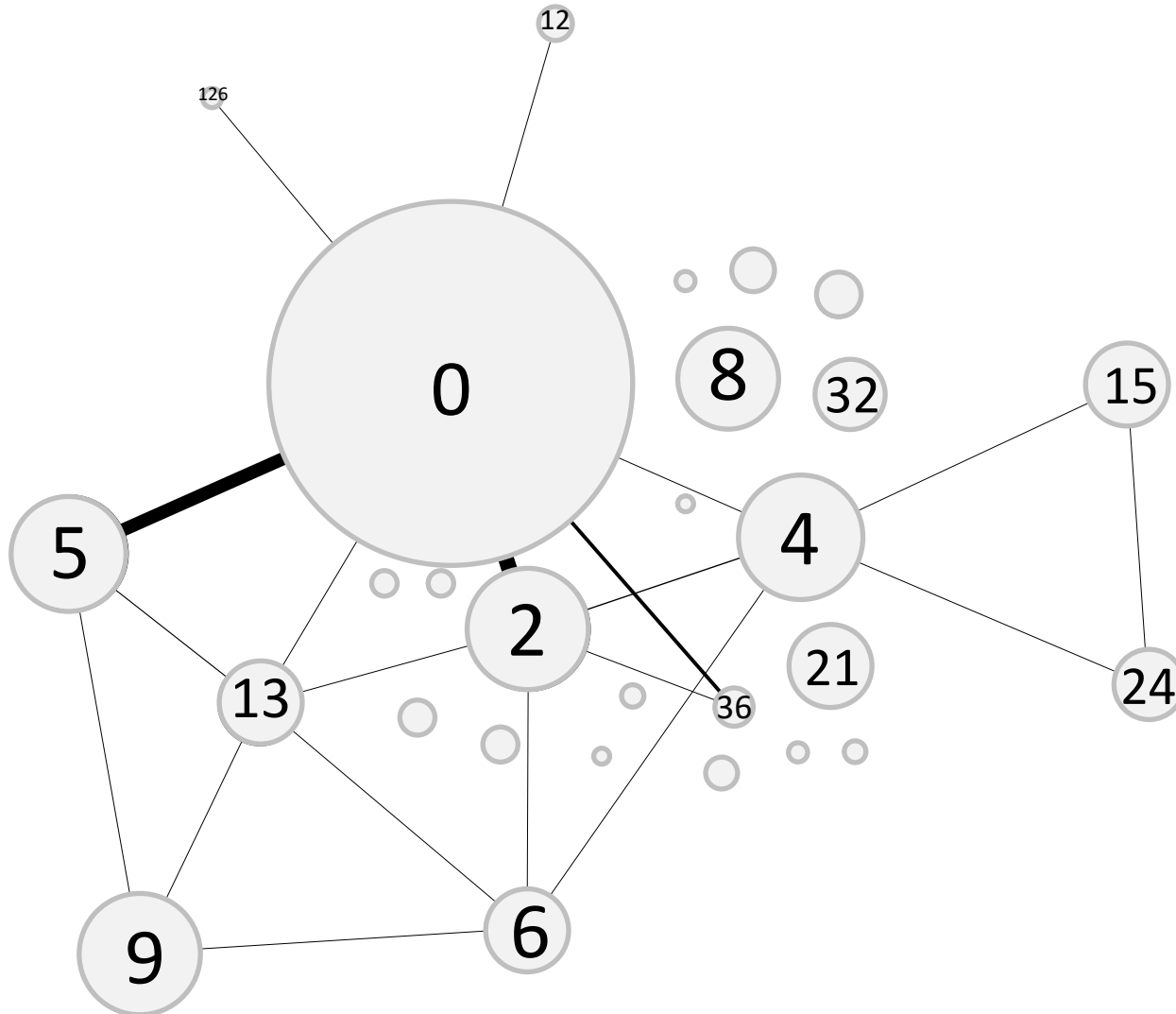


2. Co-expression network ↓



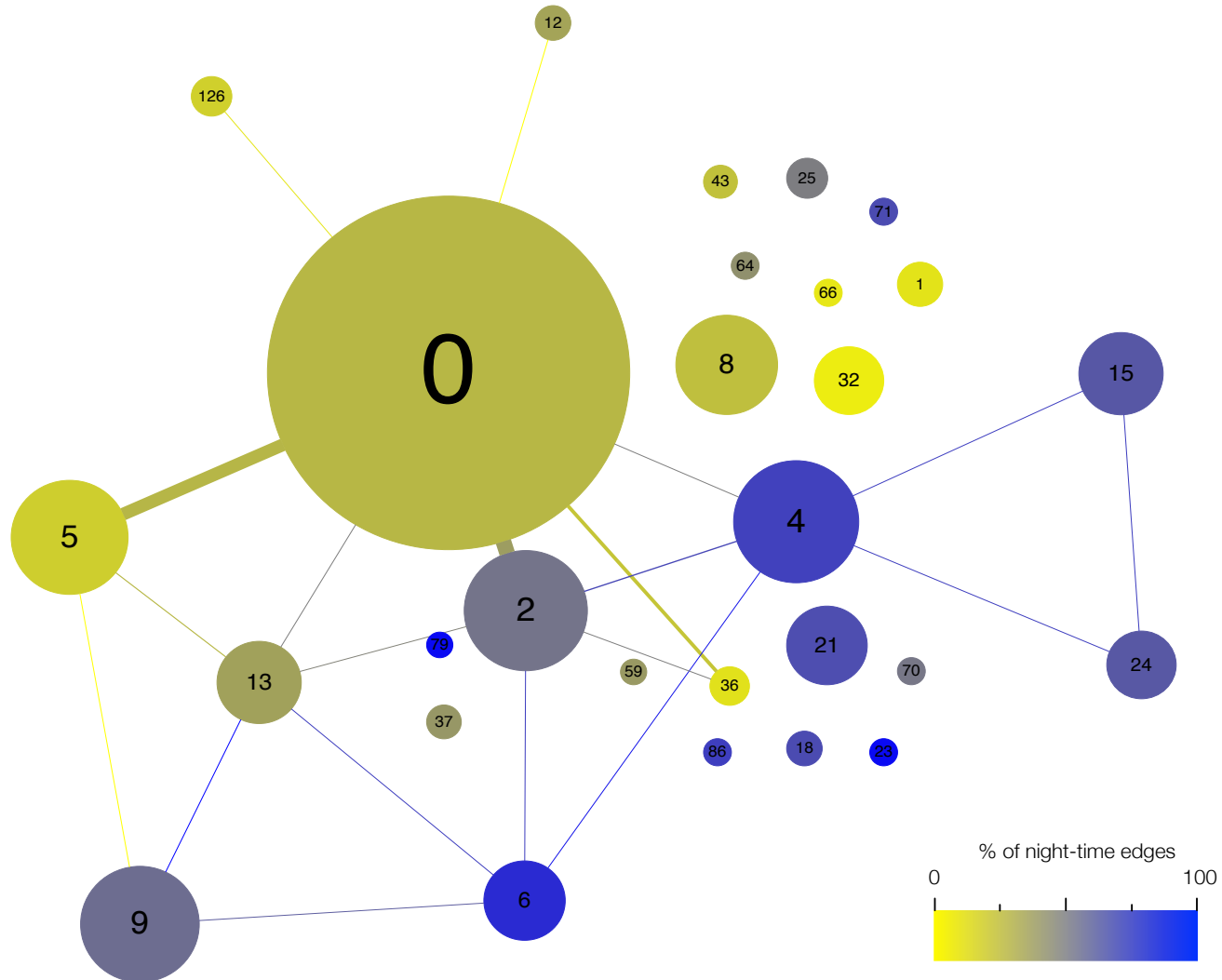
Gene Co-expression Networks

Using inter-individual gene expression variability

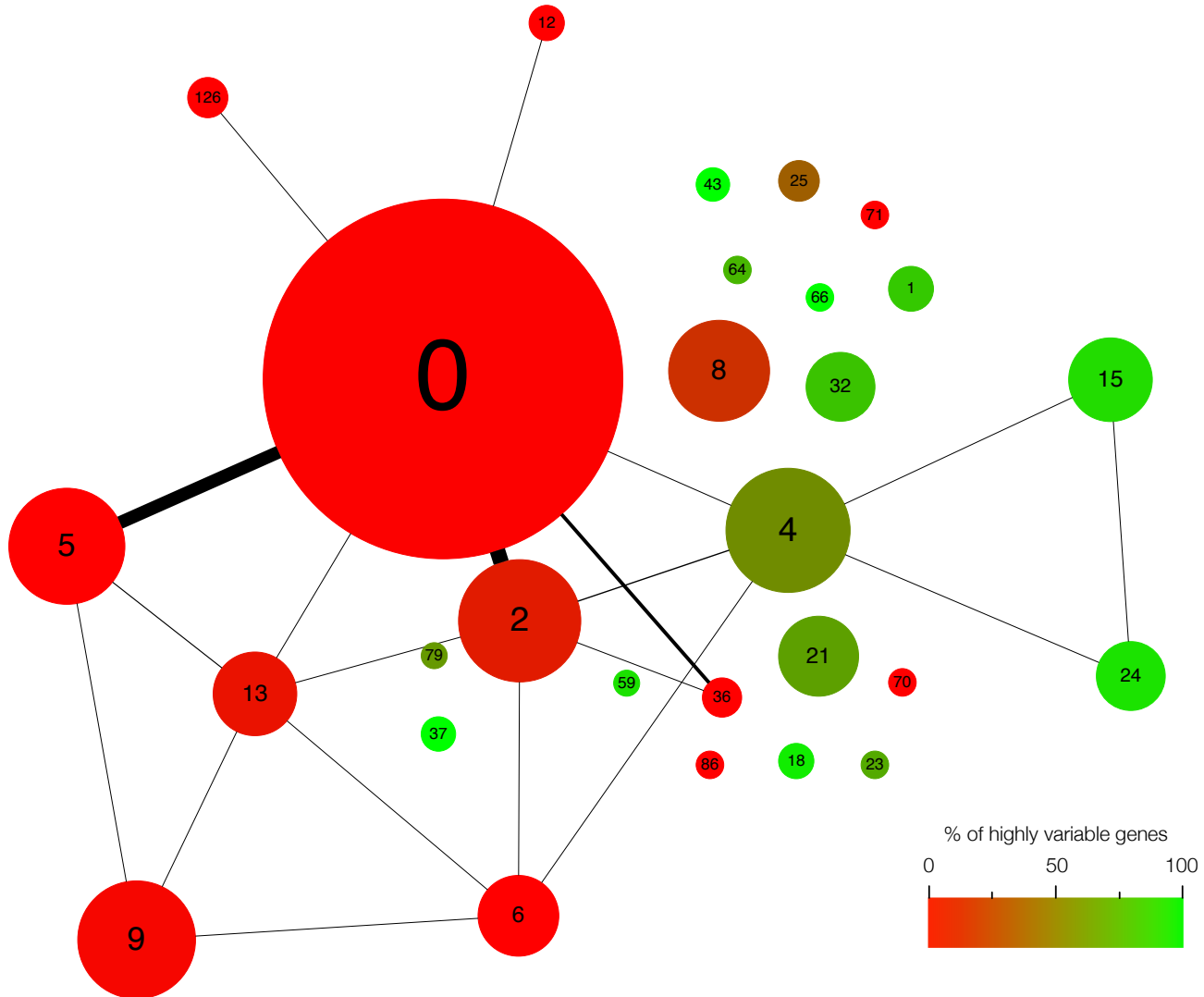


Network of 1729 genes, with 153 modules of 2 to 334 genes.

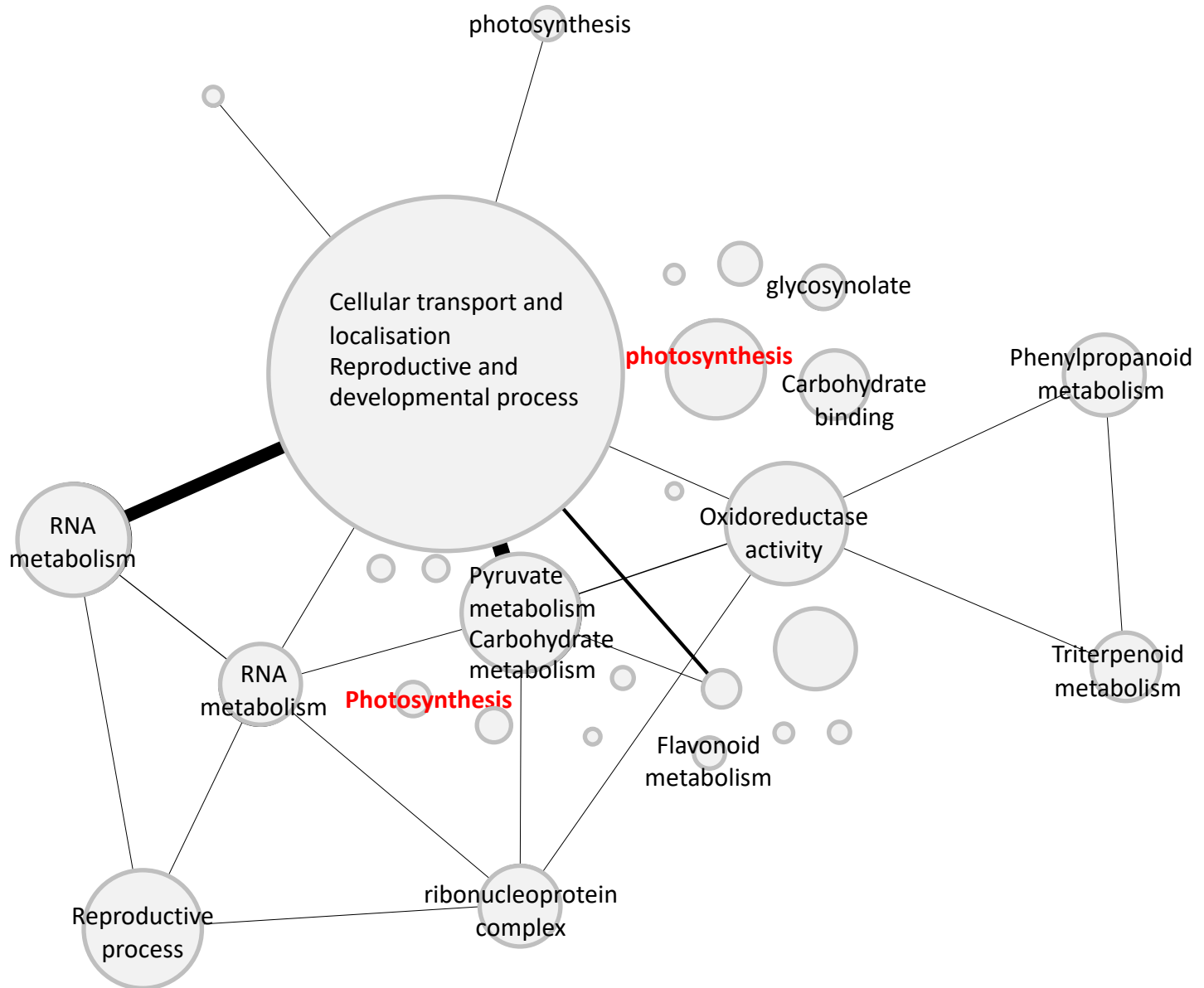
Modules structure



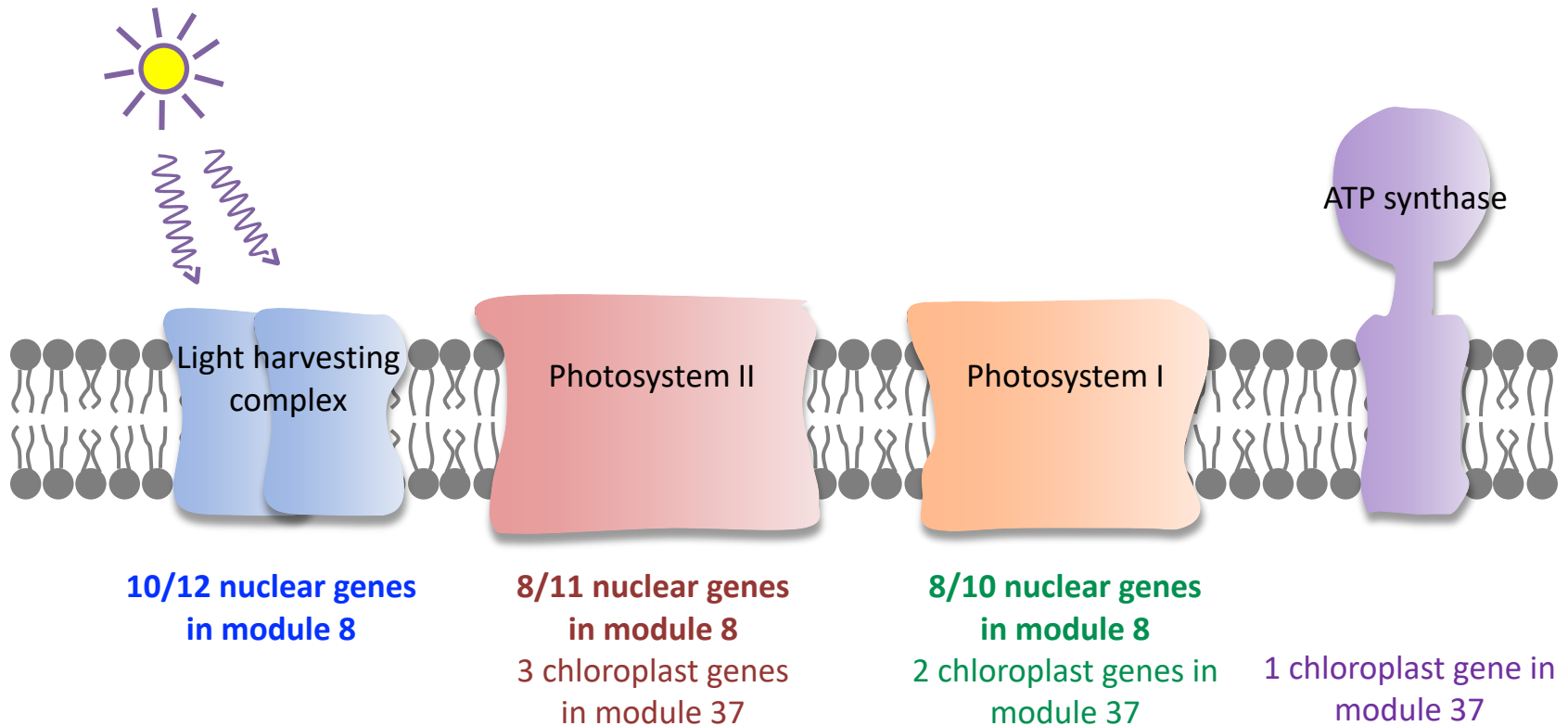
Modules structure



Functional characterisation of modules

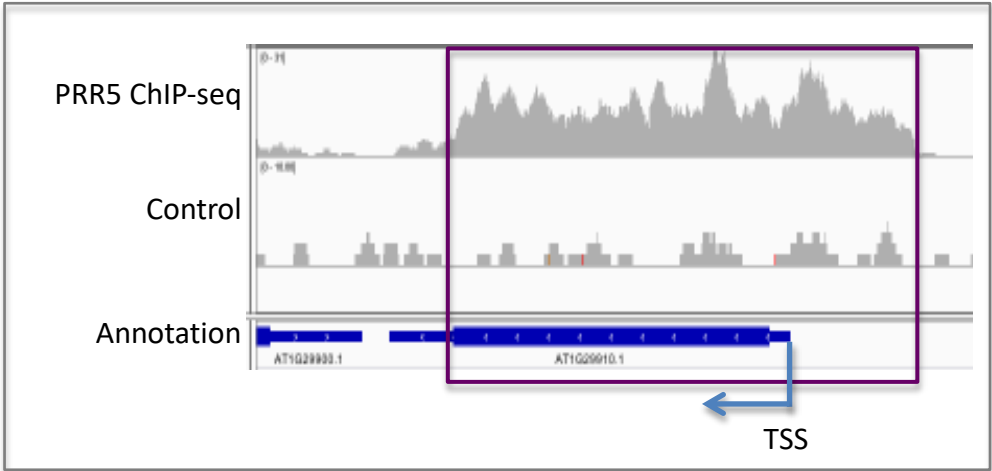
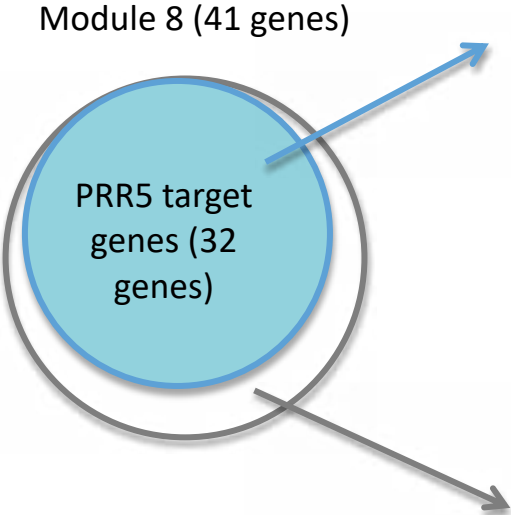


Functional characterisation of modules



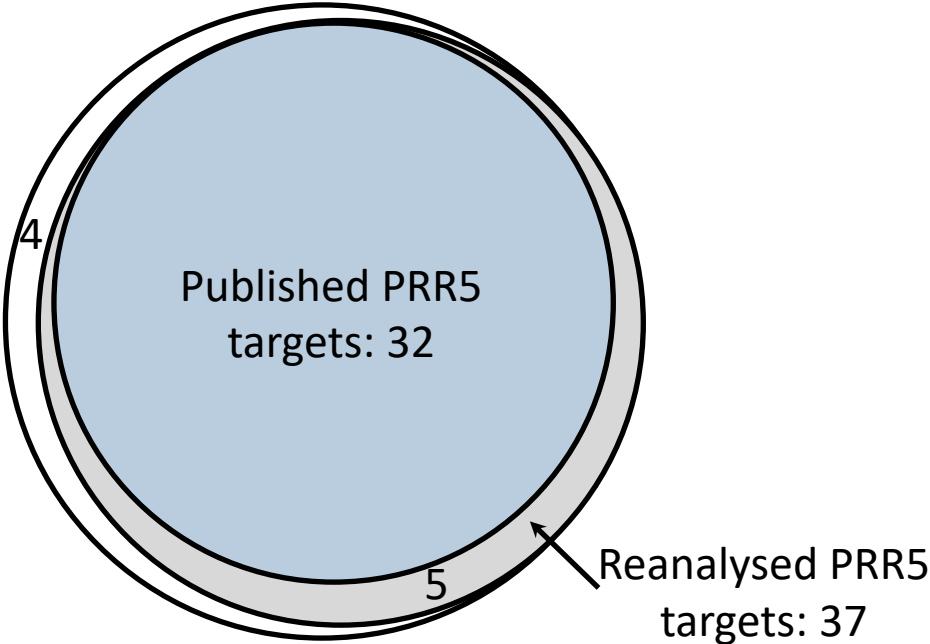
Module 8: 33/41 genes involved in photosynthesis
Module 37: 9/12 are chloroplast genes

Identification of new TF targets in modules



Identification of new TF targets in modules

Module 8 (41 genes)

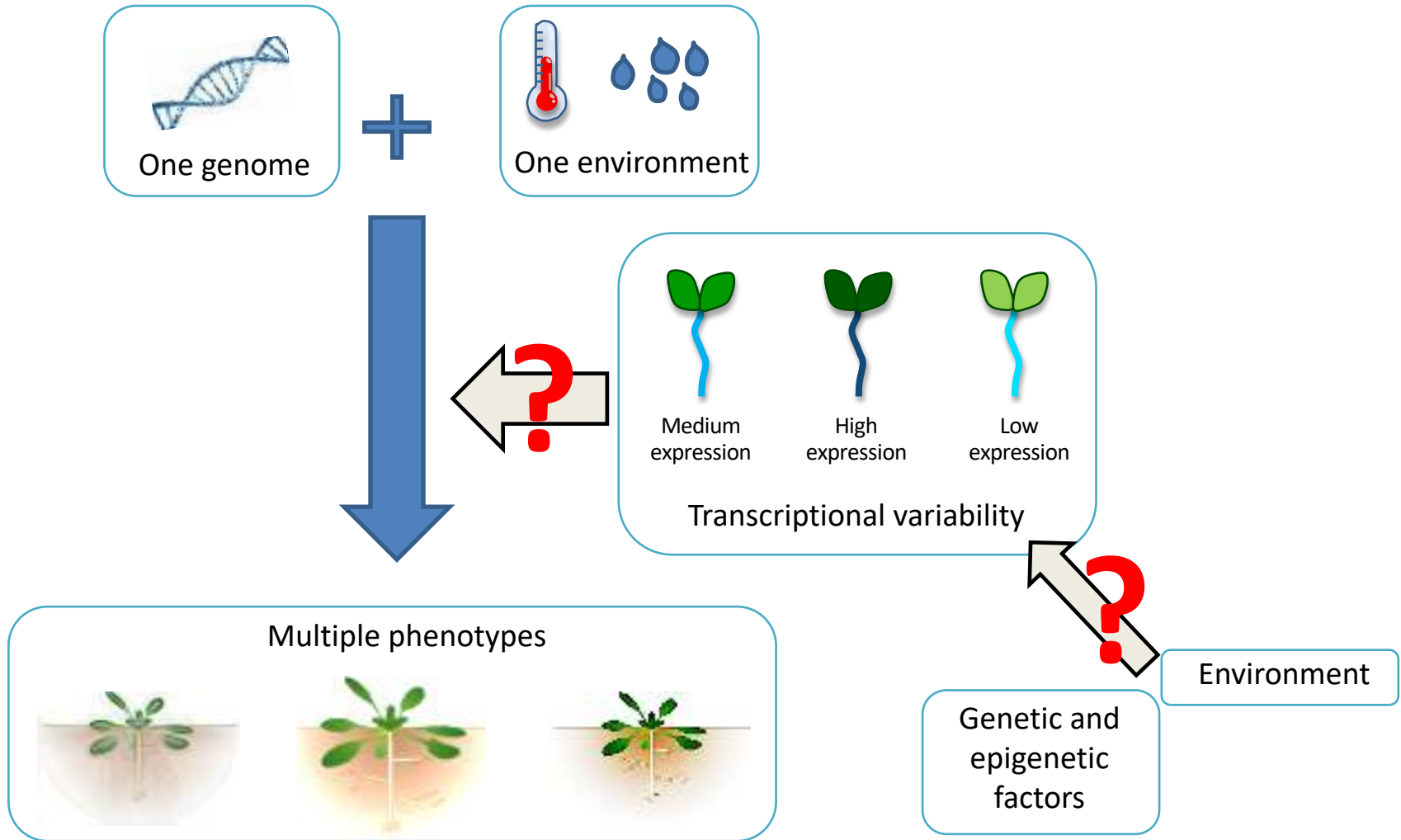


Summary

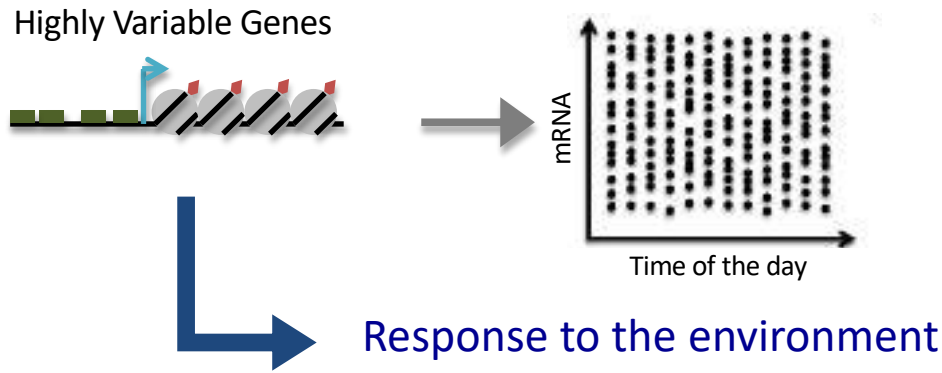
- Highly variable genes have specific features
- Gene expression variability between seedlings can be used to infer gene co-expression networks
- These networks can be used to detect new gene pathways or functions: PRR5 regulation of a not yet identified target

Website: <https://jlggroup.shinyapps.io/VariabilityNetwork/>

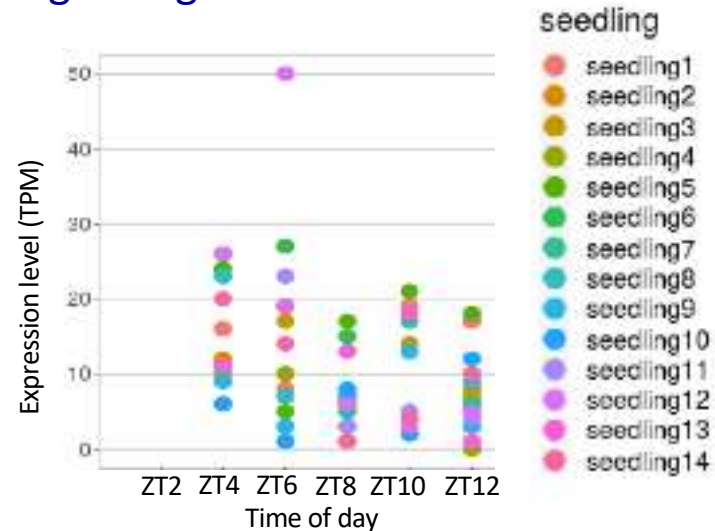
Current work



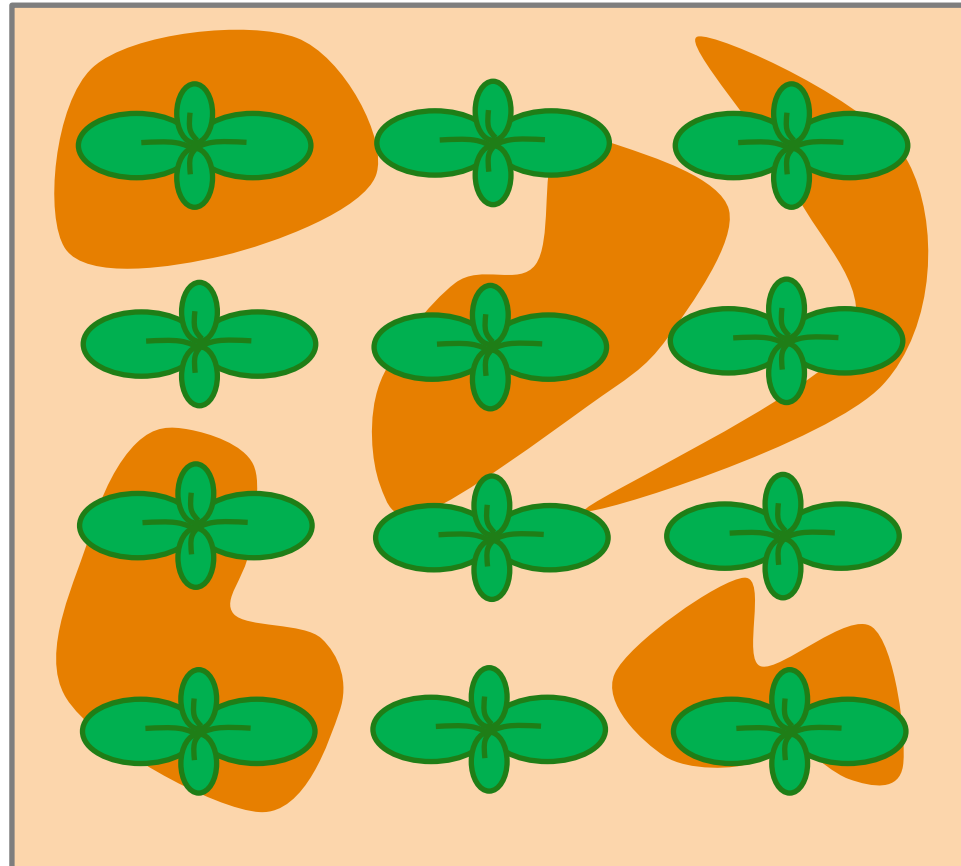
Highly variable genes are environmentally responsive



Including nitrogen nutrition

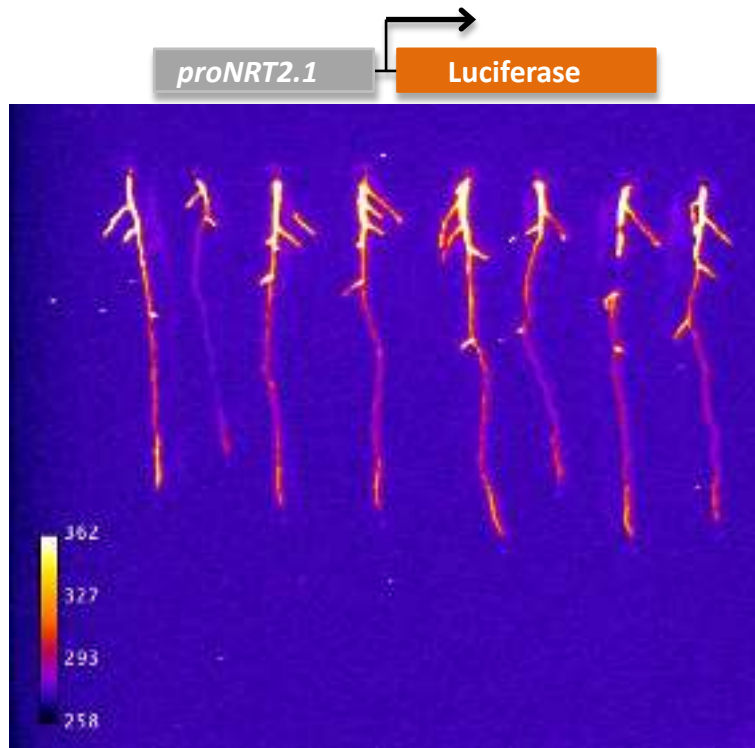


Nitrate in soil is fluctuating over time and space



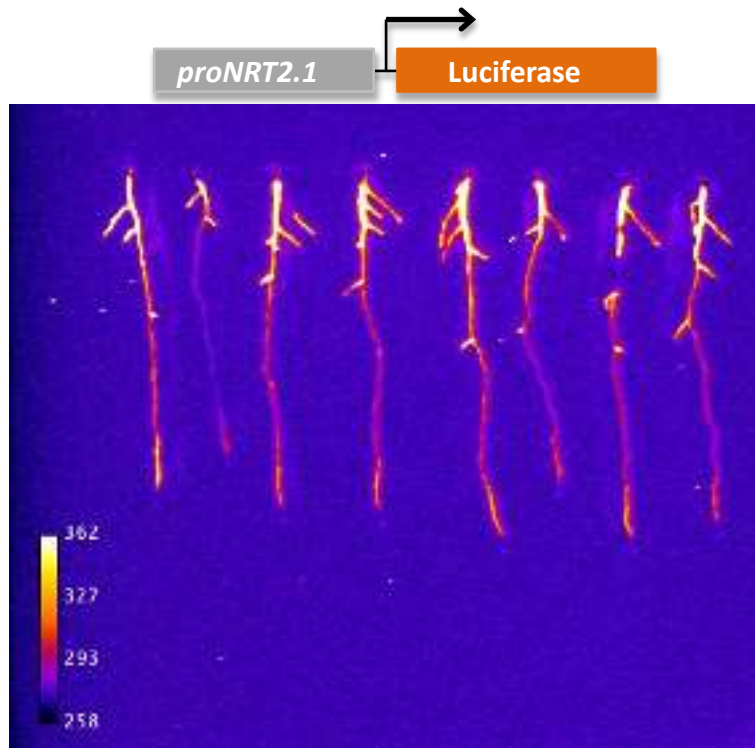
 High nitrogen patch

NRT2.1, a key nitrate transporter, is a highly variable gene



11 days old *pNRT2.1:LUC* plants on 1mM KNO_3

NRT2.1, a key nitrate transporter, is a highly variable gene



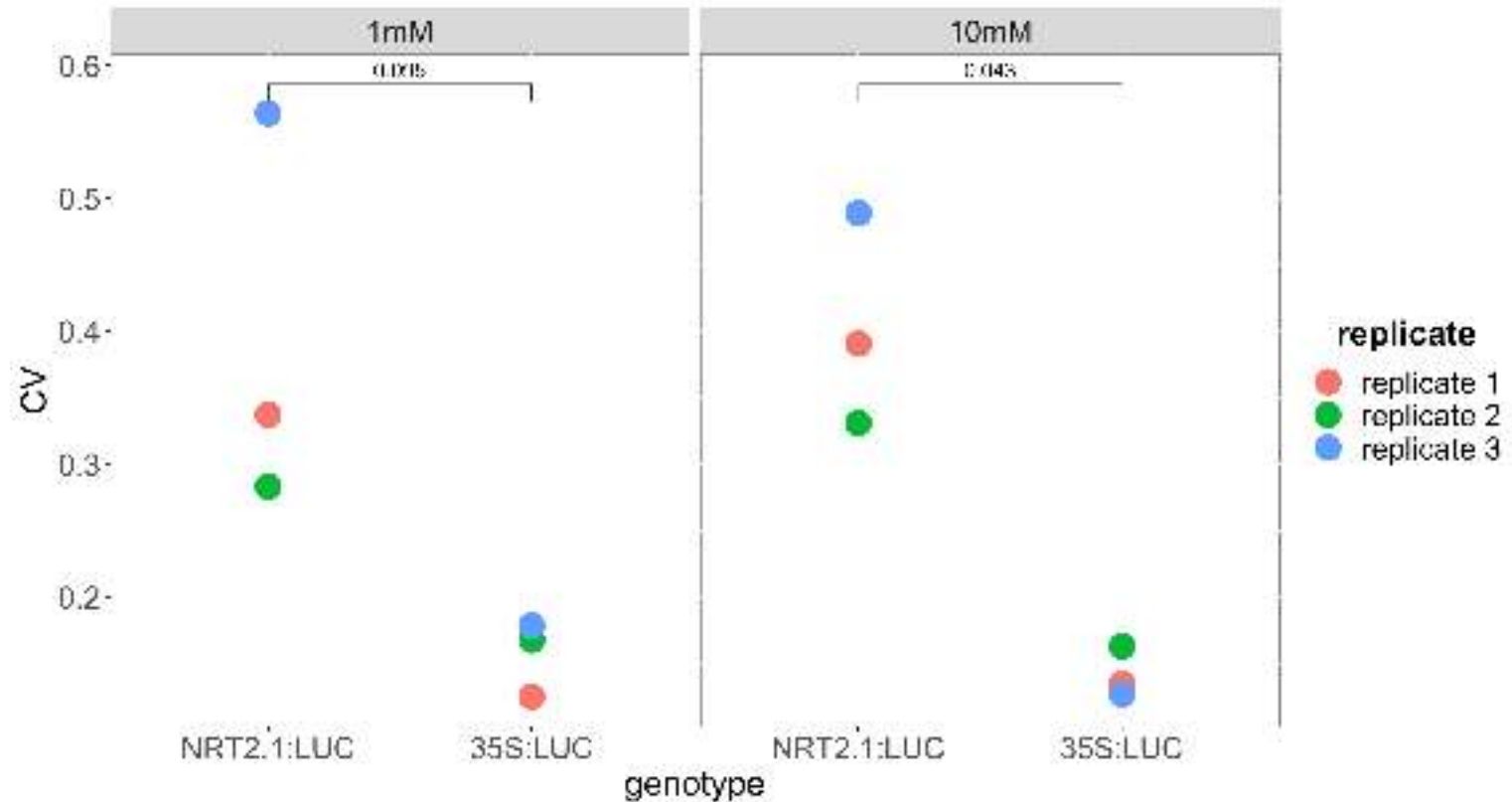
CV to measure the level of variability

CV= Standard deviation / average

(using ~30 plants)

11 days old *pNRT2.1:LUC* plants on 1mM KNO_3

NRT2.1, a key nitrate transporter, is a highly variable gene

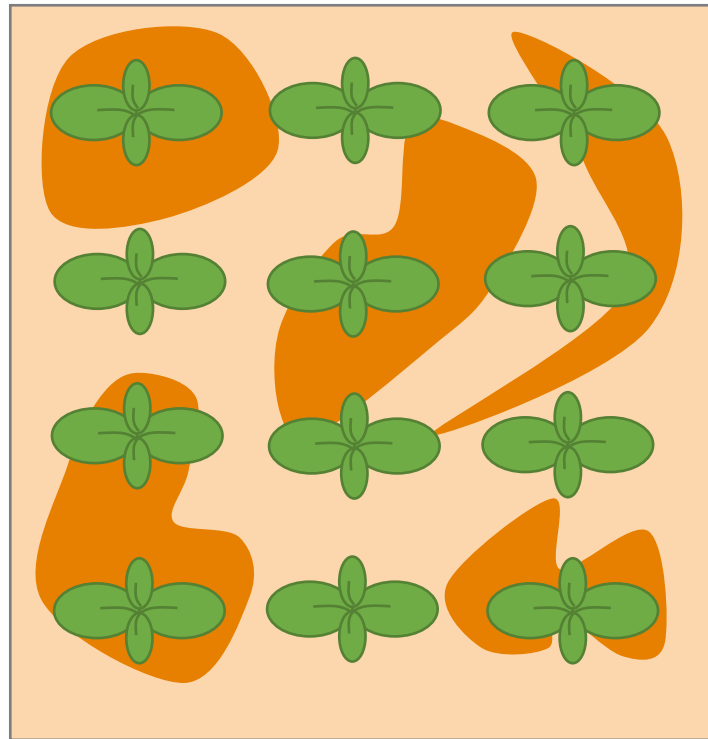


NRT2.1 is more variable than the constitutive 35S promoter

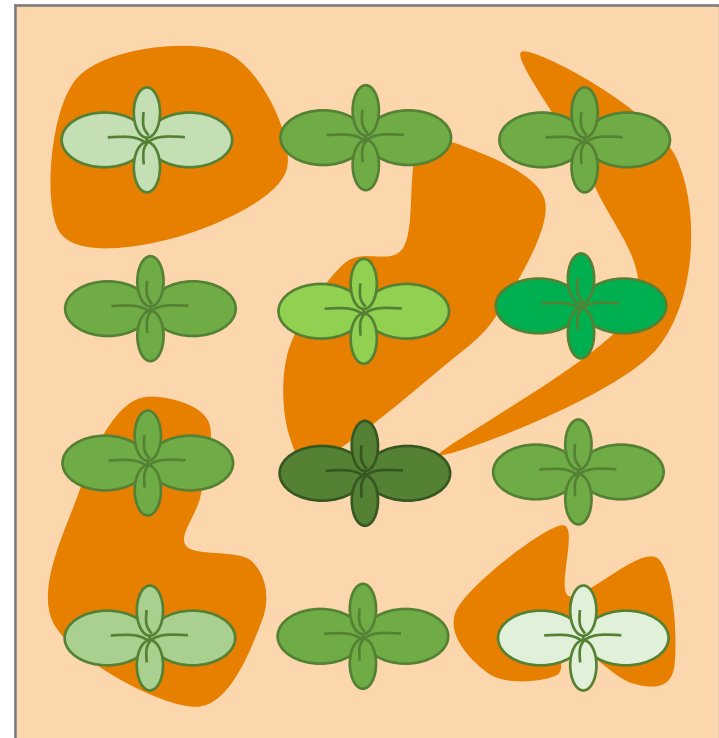
Variability can help populations of plants to survive

NRT2.1 is a highly variable gene

Nitrate in soil fluctuates temporally and spatially



Non variable population

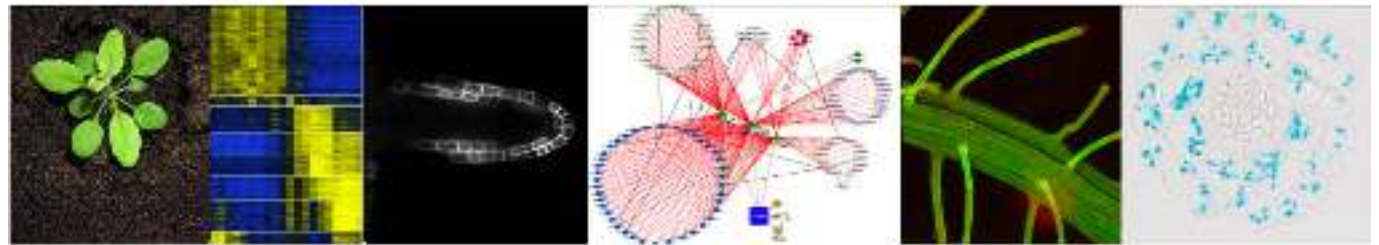


Variable population

Could variability in key genes in nitrate nutrition help plants to deal with unpredictable changes in nitrate concentration in soil?

Current work

Consequences and regulation of gene expression variability for nitrate nutrition in Arabidopsis



Nitrate signaling and regulation by the environment

Thanks!

James Locke group (SLCU)

Marcel Bhattarai

Zeynep Aydin



Sebastian Ahnert (SLCU)

Antoine Martin's group (BPMP)

Kenneth Schöneck

Oscar Main



Tou Cheu Xiong (BPMP)