

NON-LINEAR PLANT PHENOTYPING PIPELINES:

HOW CAN **STRUCTURAL MODELS**
AND **MACHINE LEARNING** CAN HELP
US ANALYSE LARGE **PLANT IMAGE**
DATASETS

Guillaume Lobet, Manu Noll, Jonathan Atkinson, Darren Wells,
Xavier Draye, Patrick Thaon, Iko Koevoets,
Shehan Marandage, Mirjam Zorner

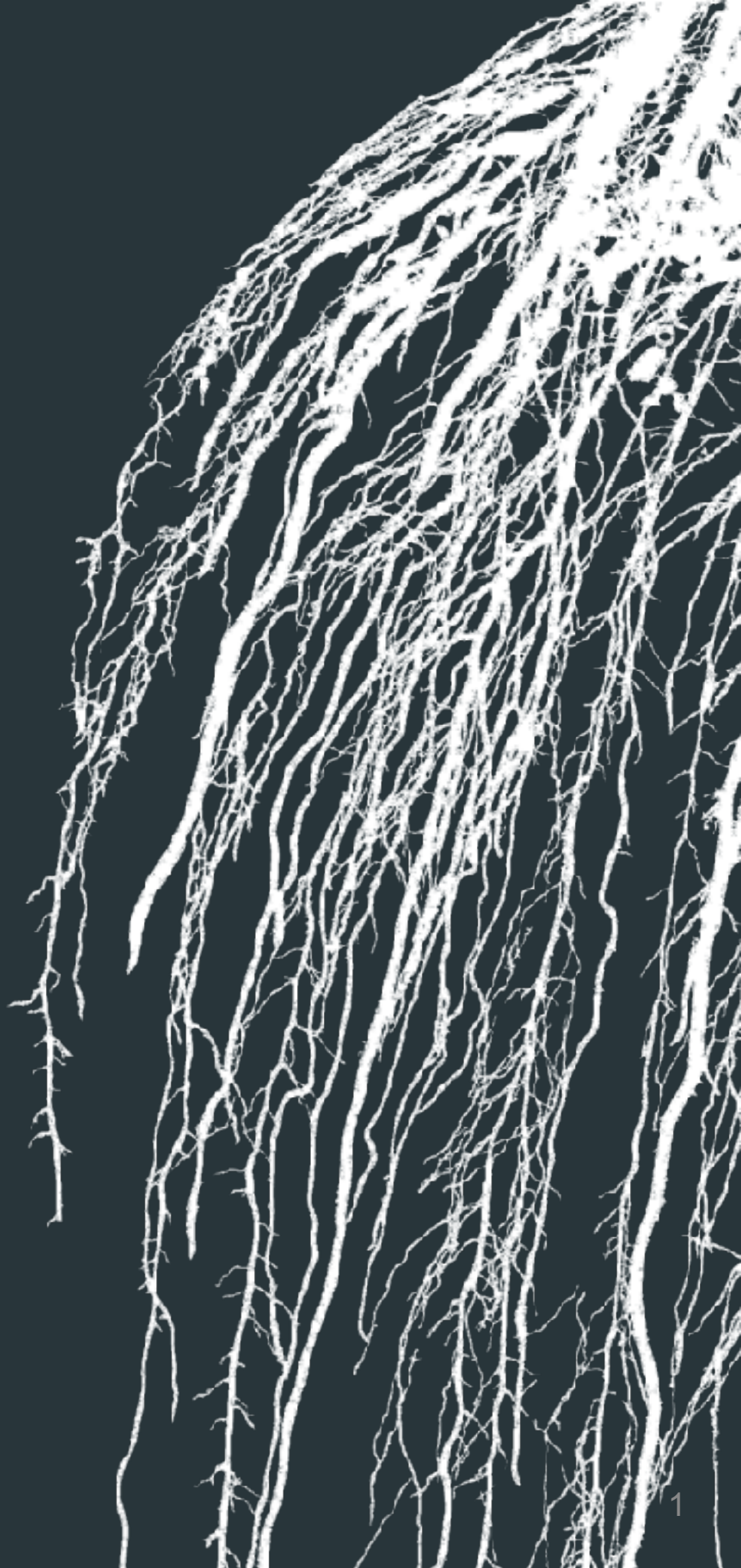
 **PHENOME 2018**
TUCSON, AZ FEBRUARY 14-17

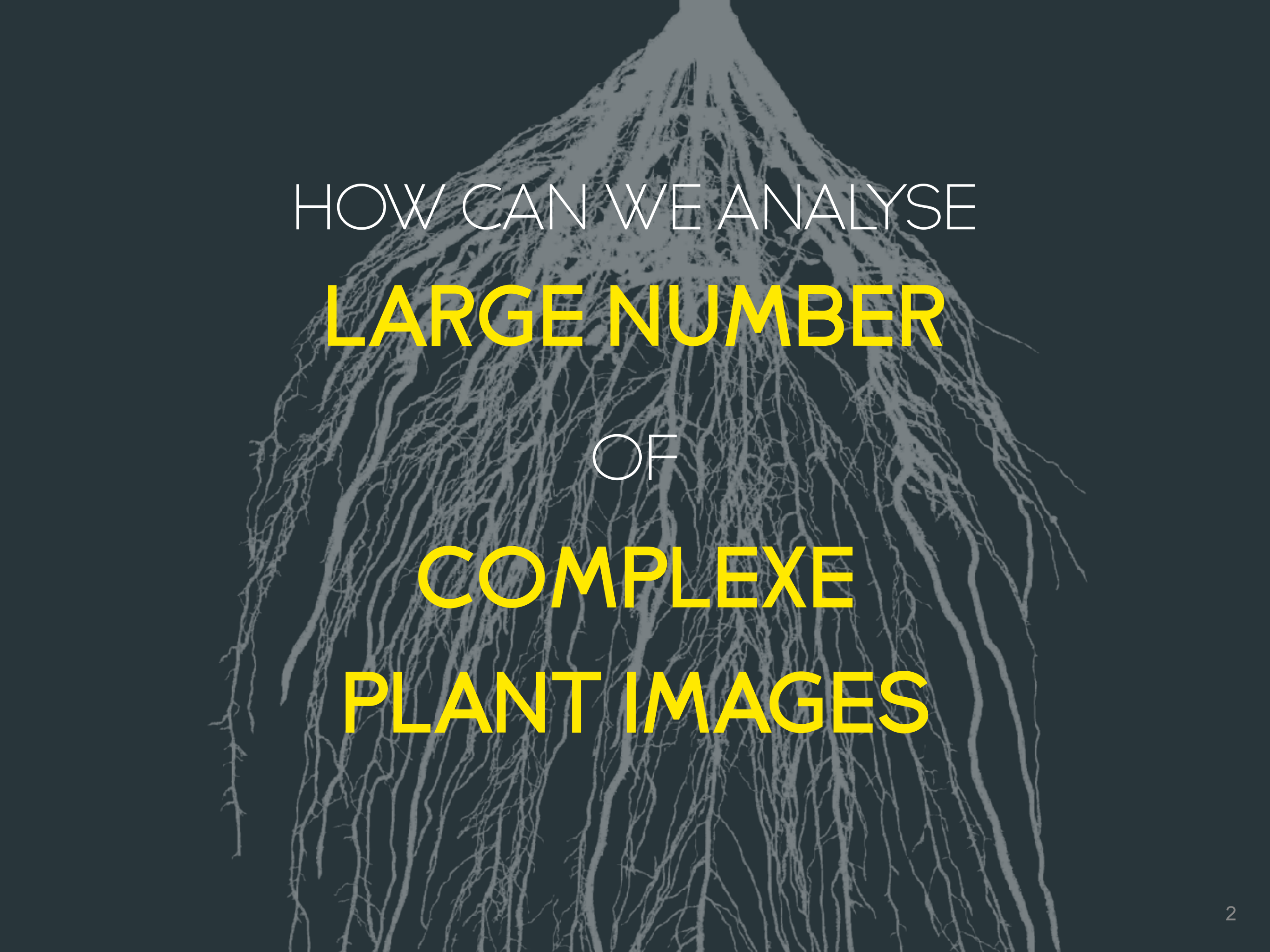
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 [@guillaumelobet](https://twitter.com/guillaumelobet)





HOW CAN WE ANALYSE

LARGE NUMBER

OF

COMPLEXE

PLANT IMAGES

IMAGE ANALYSIS



IMAGE ROOT ANALYSIS MODELS



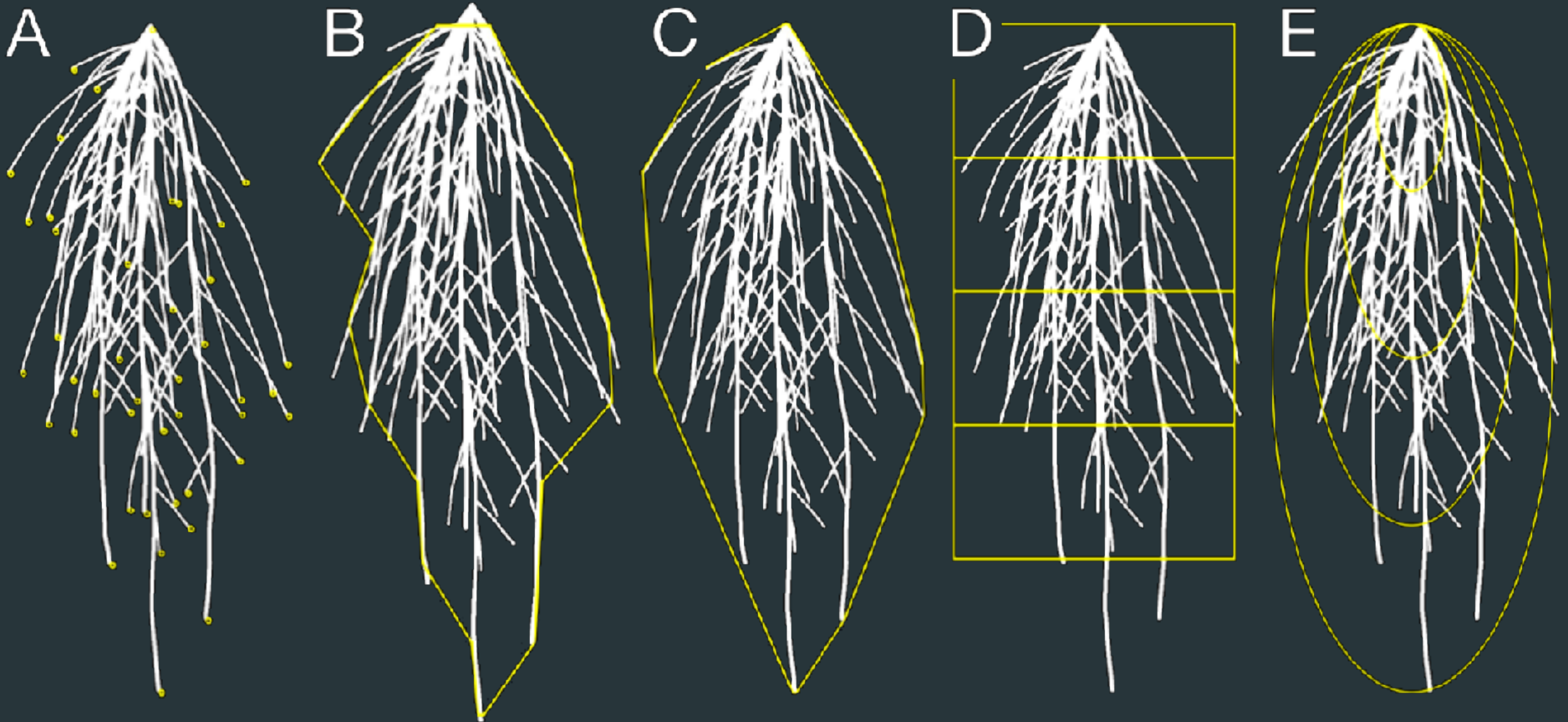
IMAGE ROOT ANALYSIS MODELS



MACHINE LEARNING



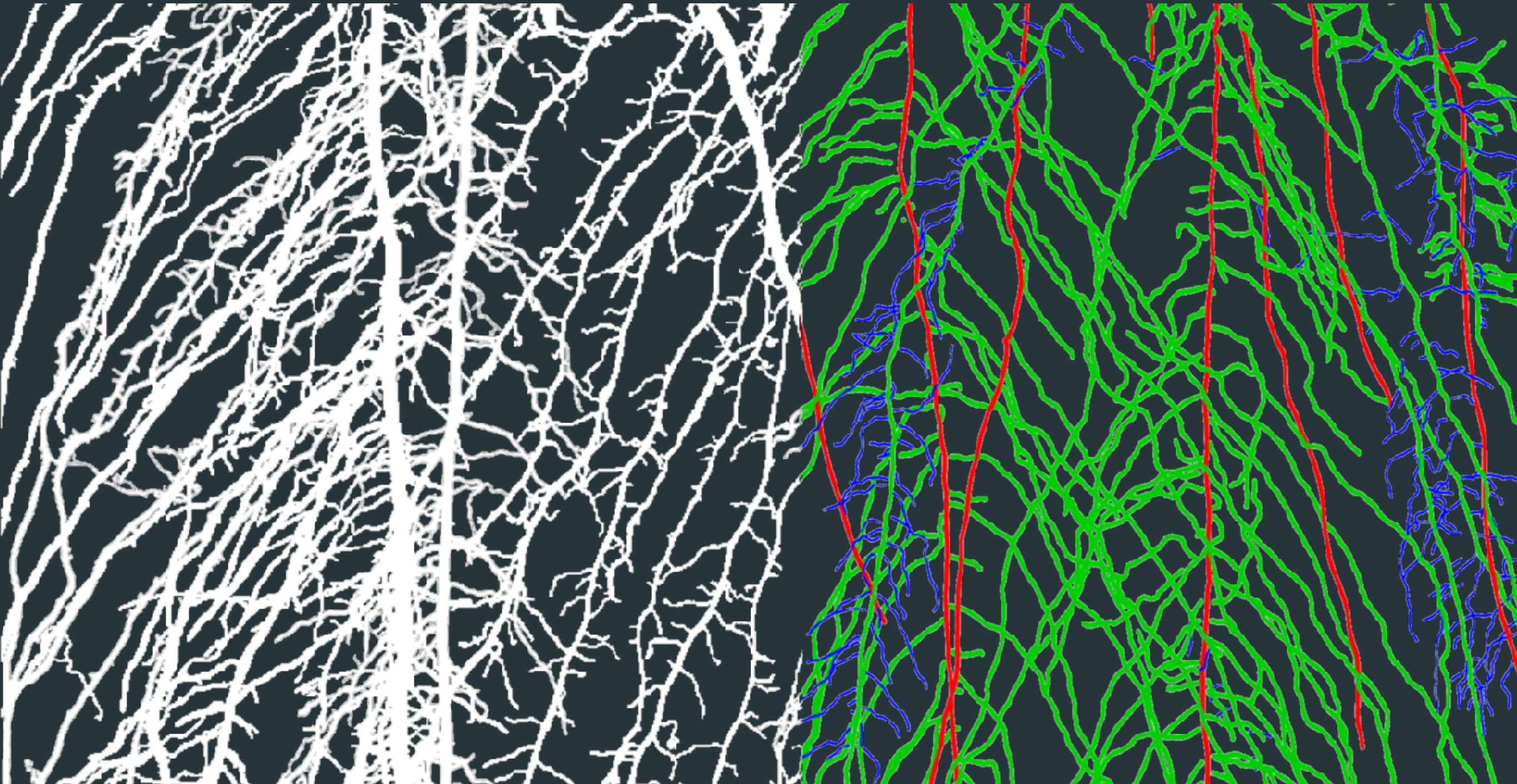
CHEAP VARIABLES = AUTOMATED



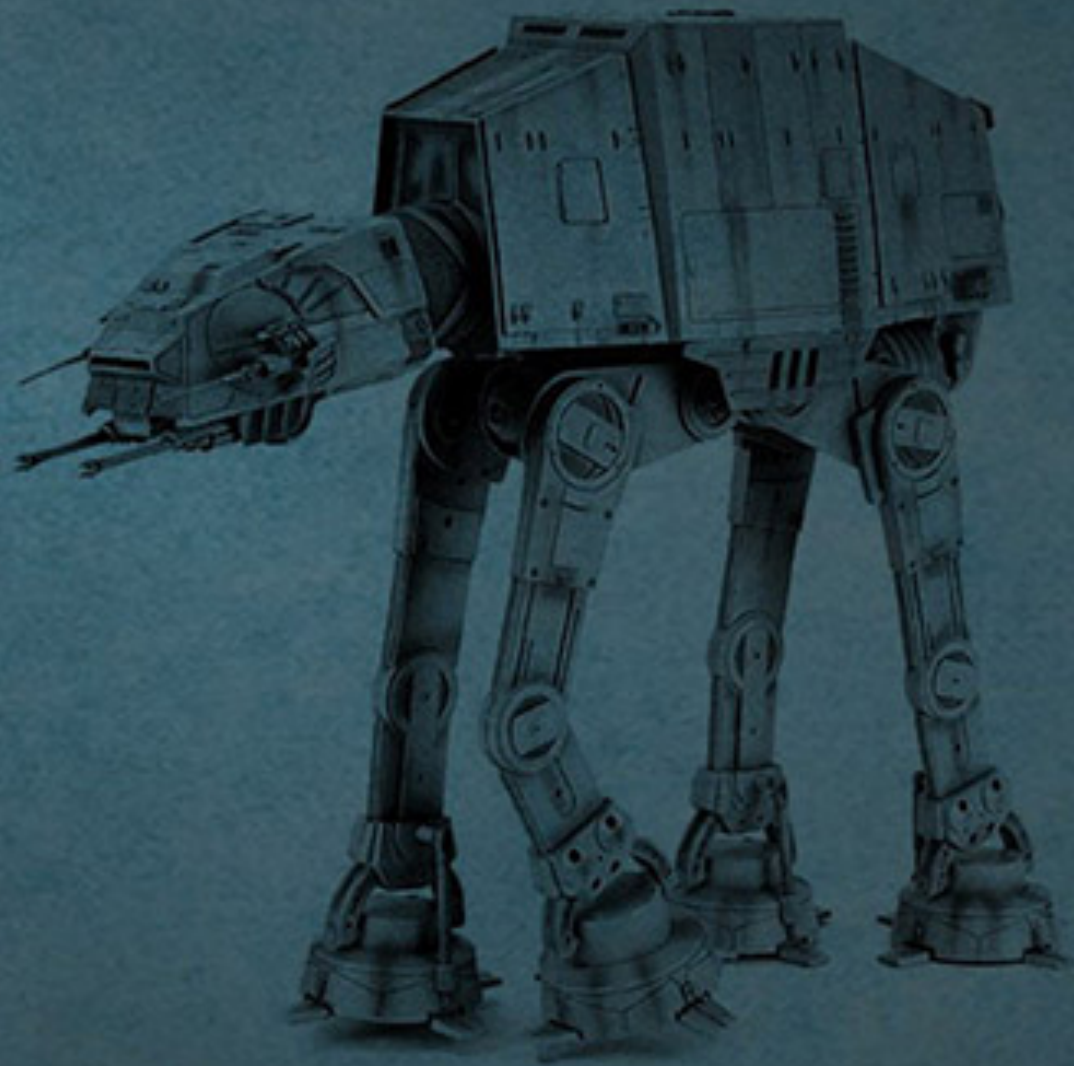
DIRT | WINRHIZO | **RIA-J** | GIA-ROOT | ROOTGRAPH



EXPENSIVE VARIABLES = **MANUAL**



SMARTROOT | DART | **ROOTNAV** | EZ-RHIZO



WINTER
IS
COMING

AT-AT

HOW CAN
WE GET
THE
BEST
OF BOTH
WORLDS?

IMAGE
ANALYSIS



ROOT
MODELS

1



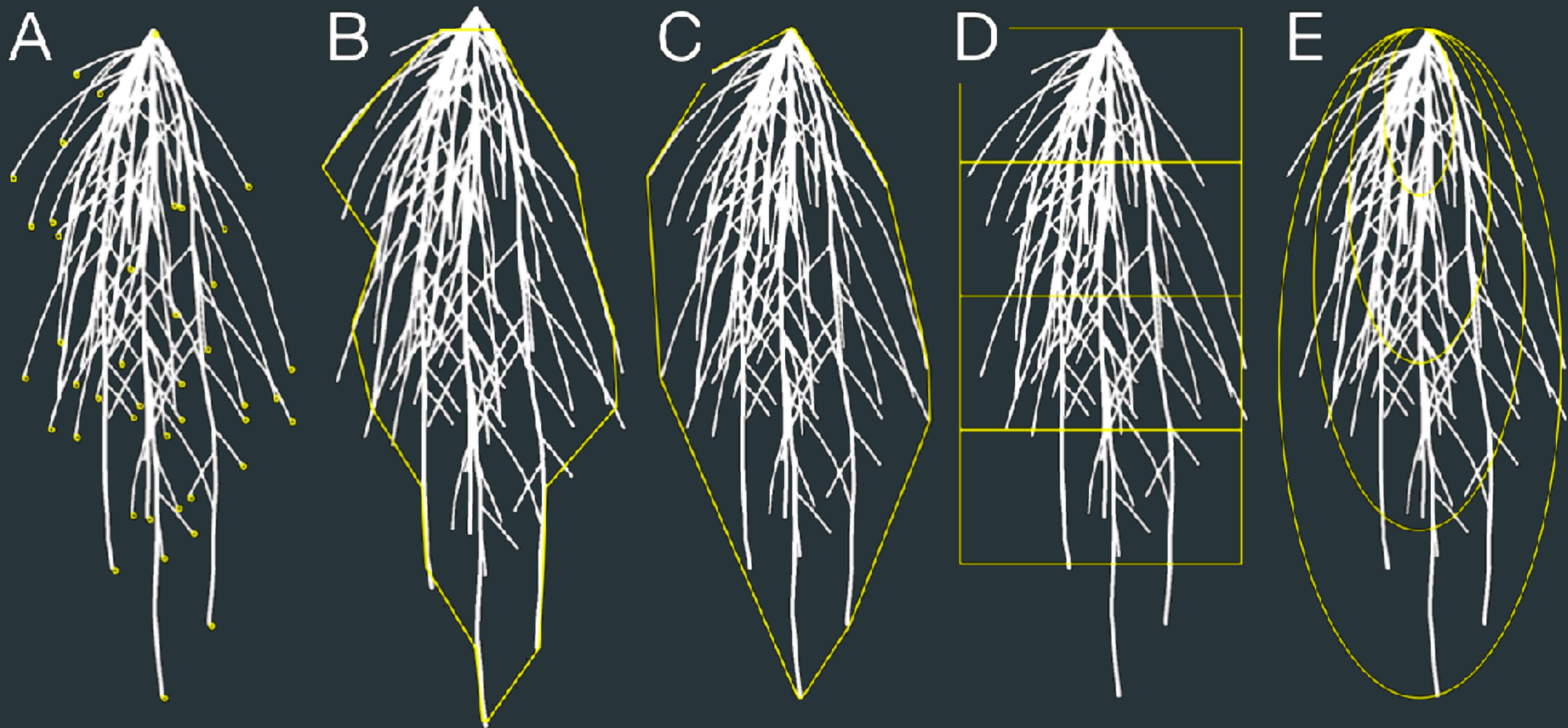
MACHINE
LEARNING

SIMULATED ROOT IMAGE **LIBRARY**

bit.ly/root-lib

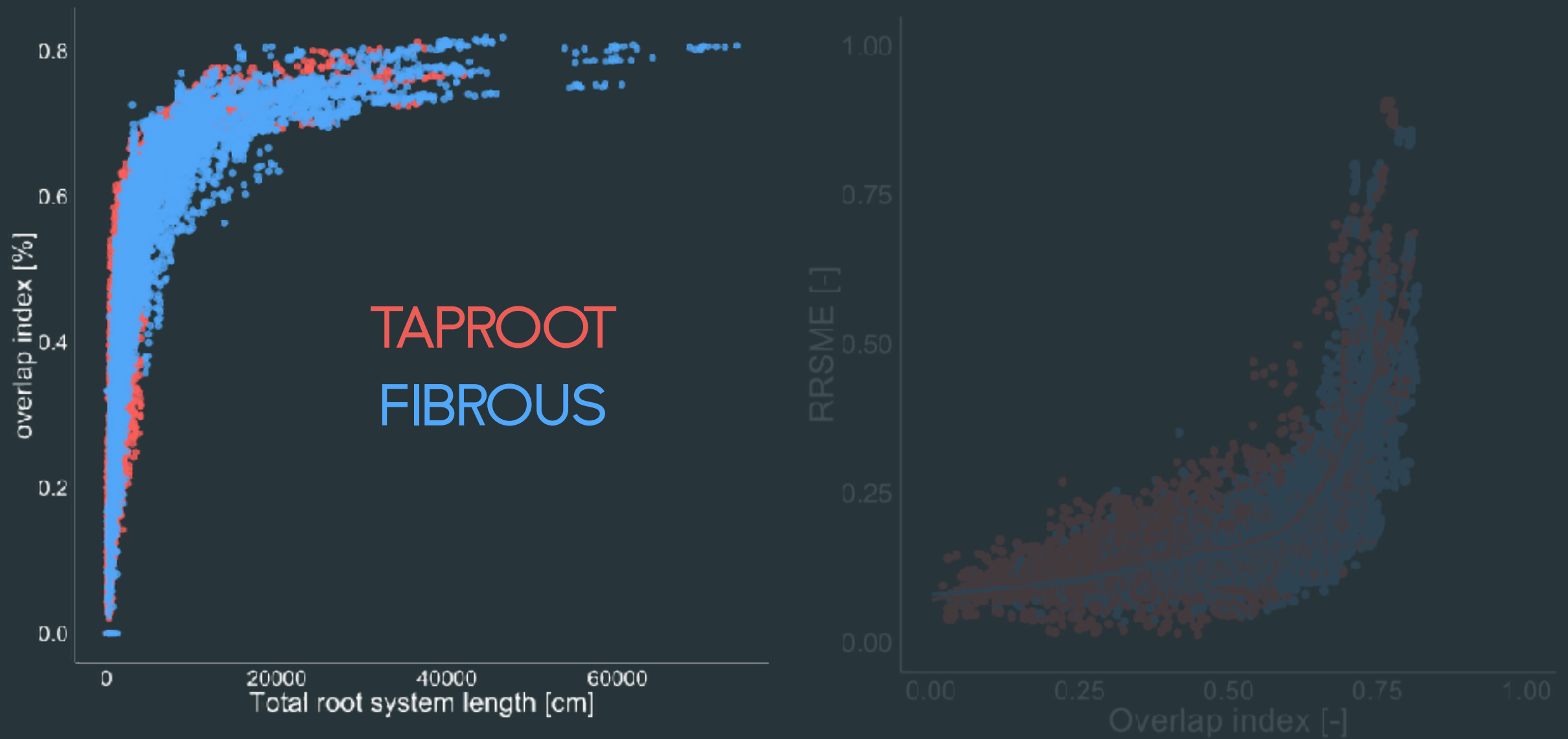


WE EXTRACT **CHEAP VARIABLES**



COMPARED WITH **GROUND-TRUTH**

ERROR INCREASES WITH SIZE



ERROR INCREASES WITH SIZE

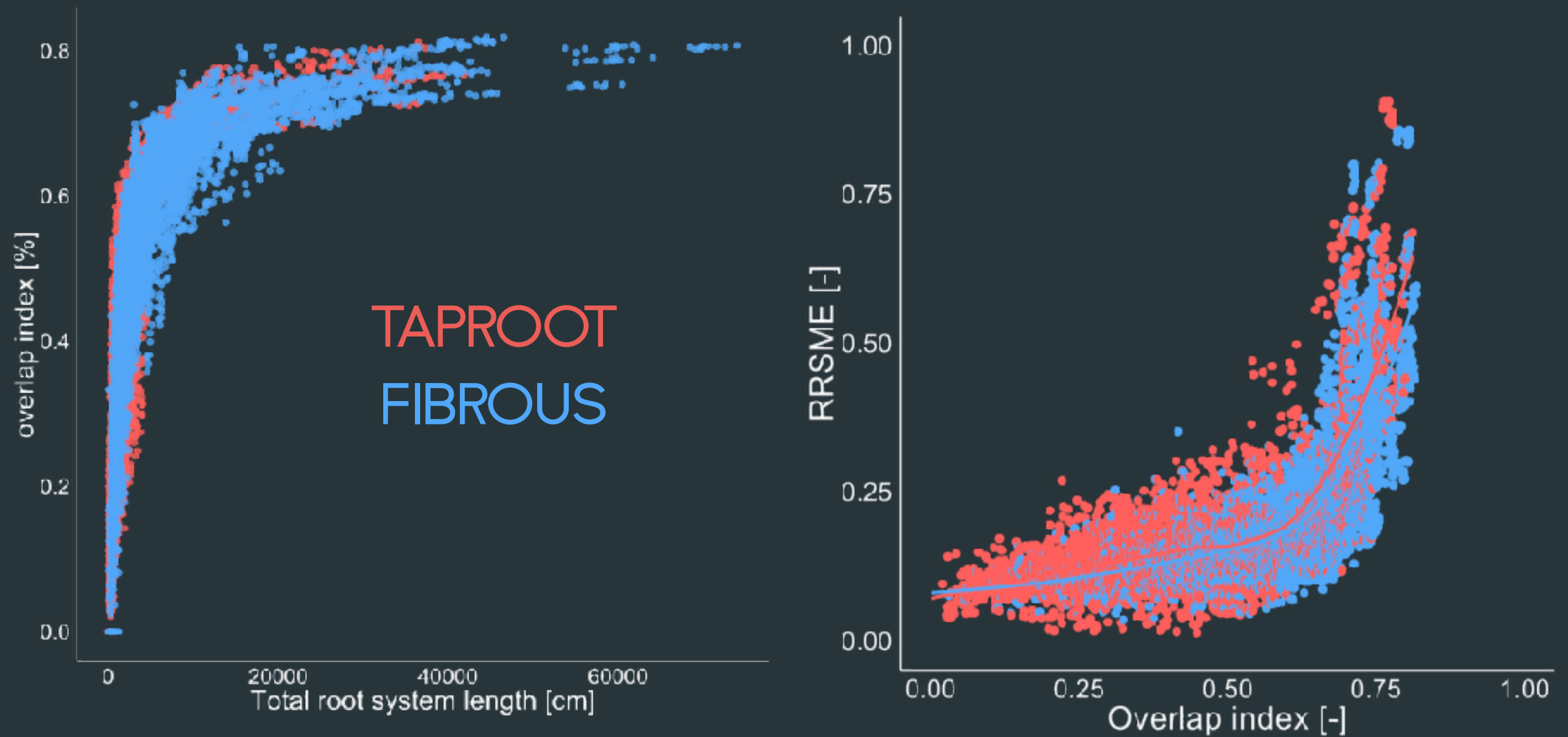


IMAGE
ANALYSIS



ROOT
MODELS



MACHINE
LEARNING

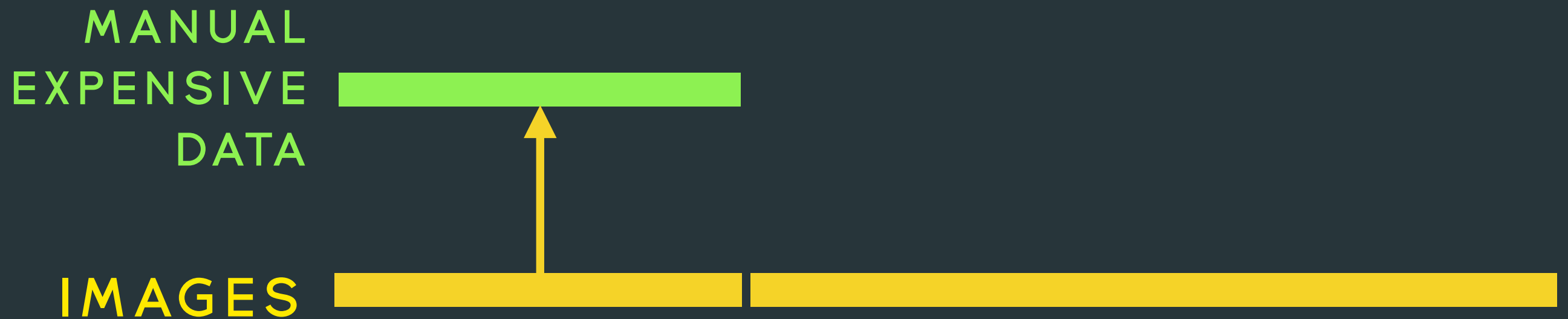
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MACHINE LEARNING ASSISTED ANALYSIS

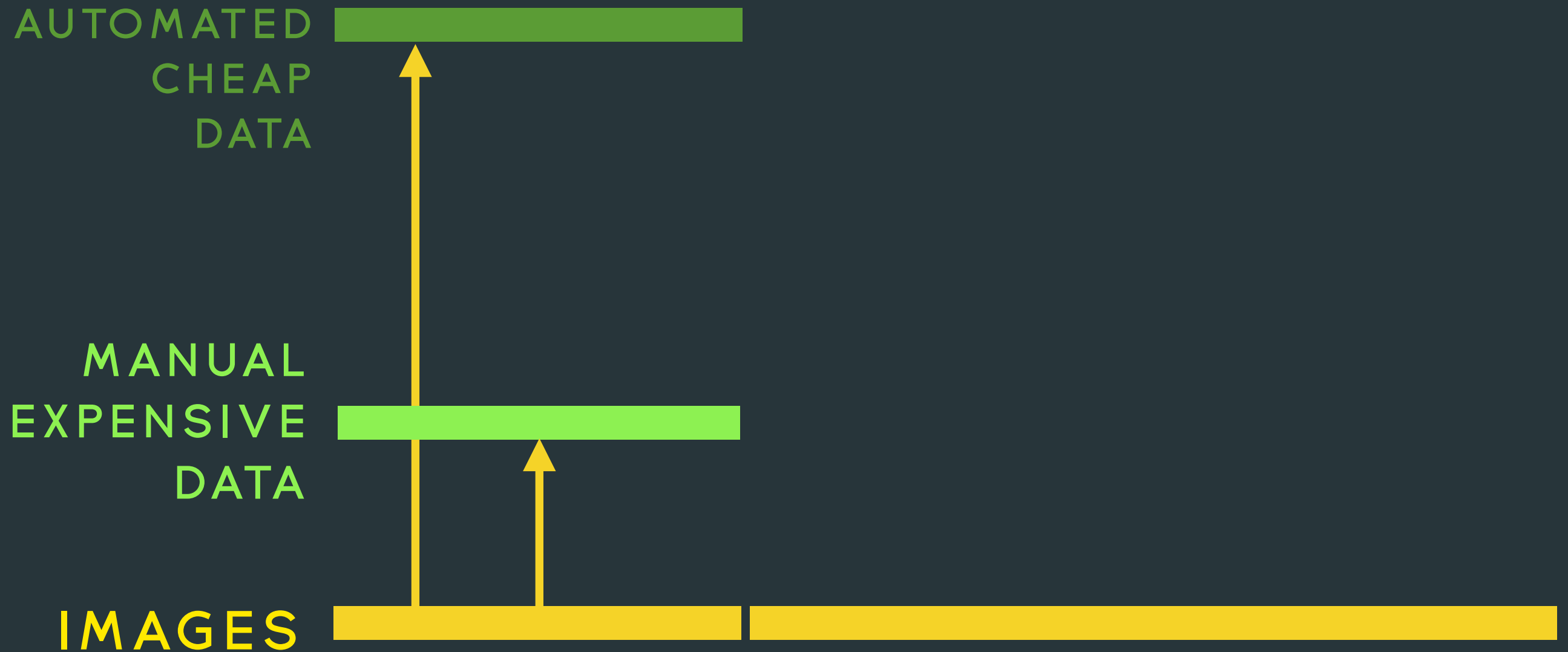
IMAGES



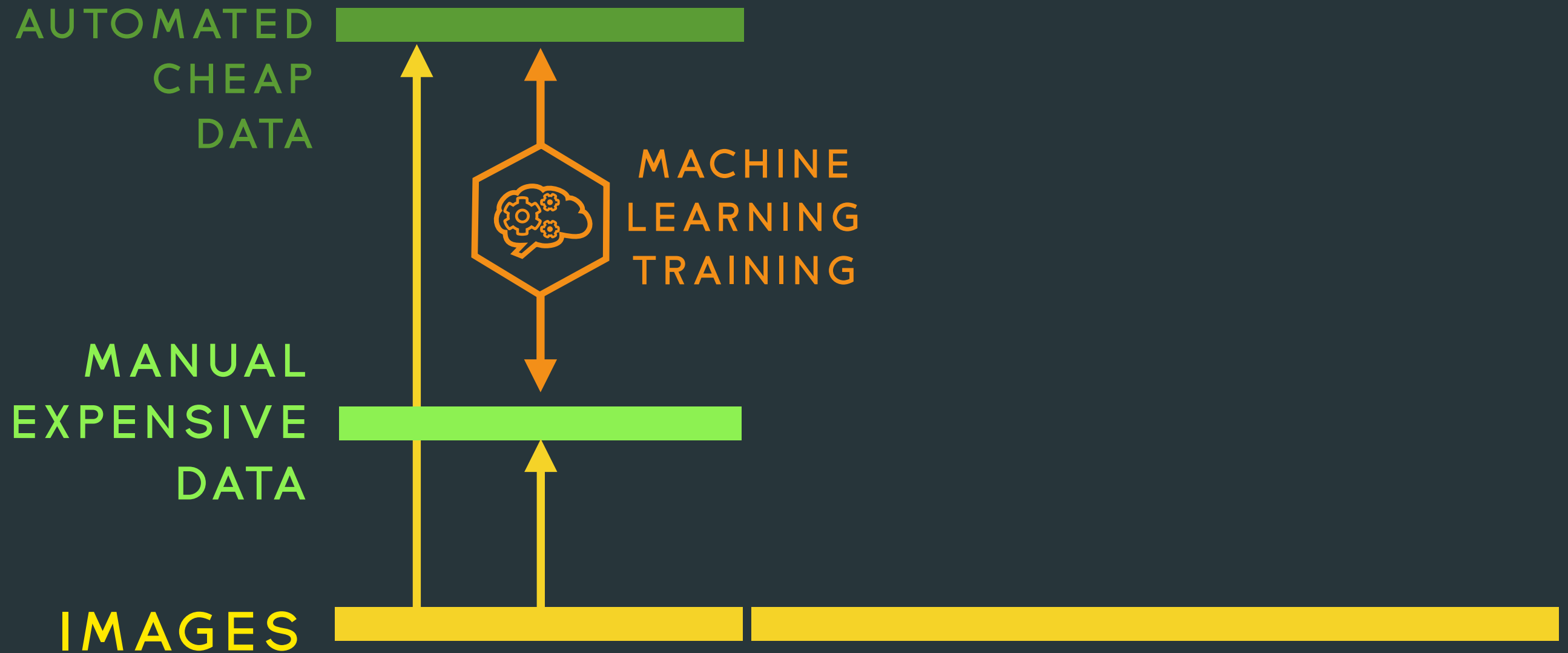
MACHINE LEARNING ASSISTED ANALYSIS



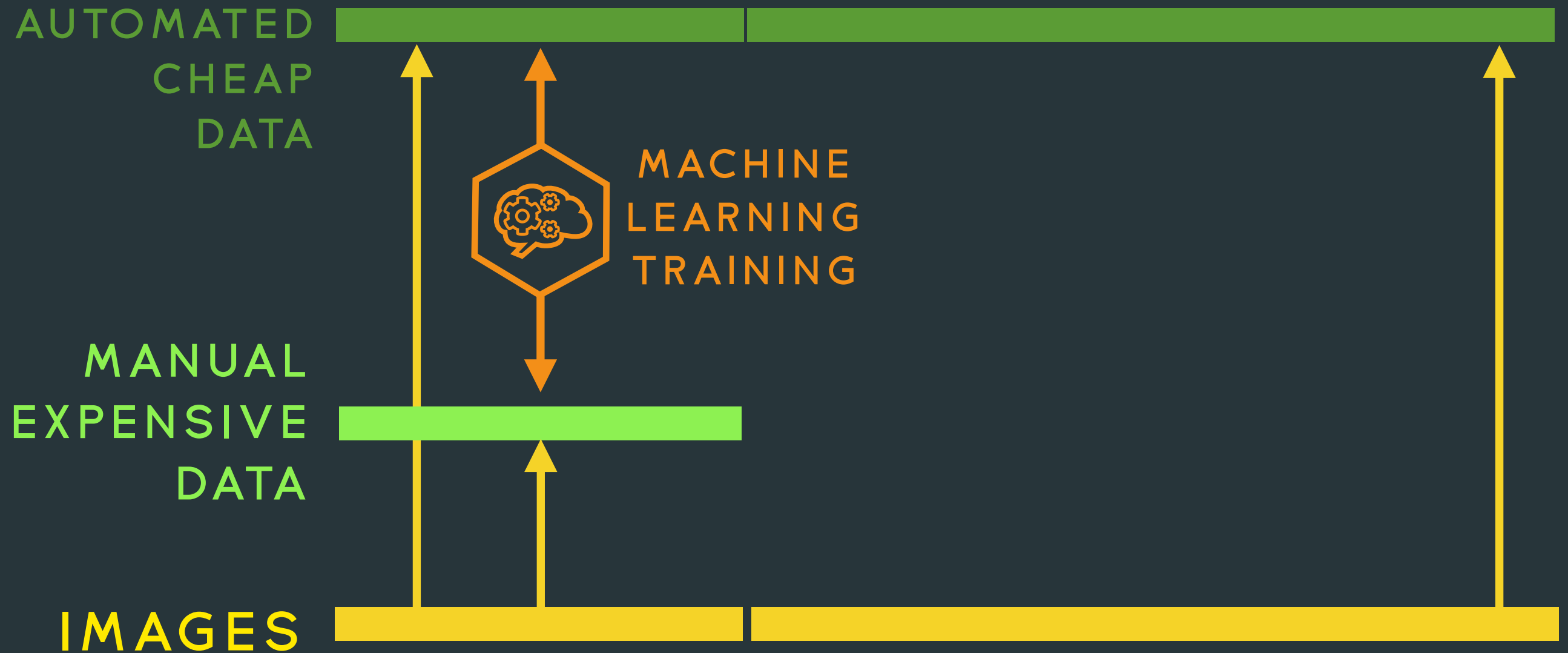
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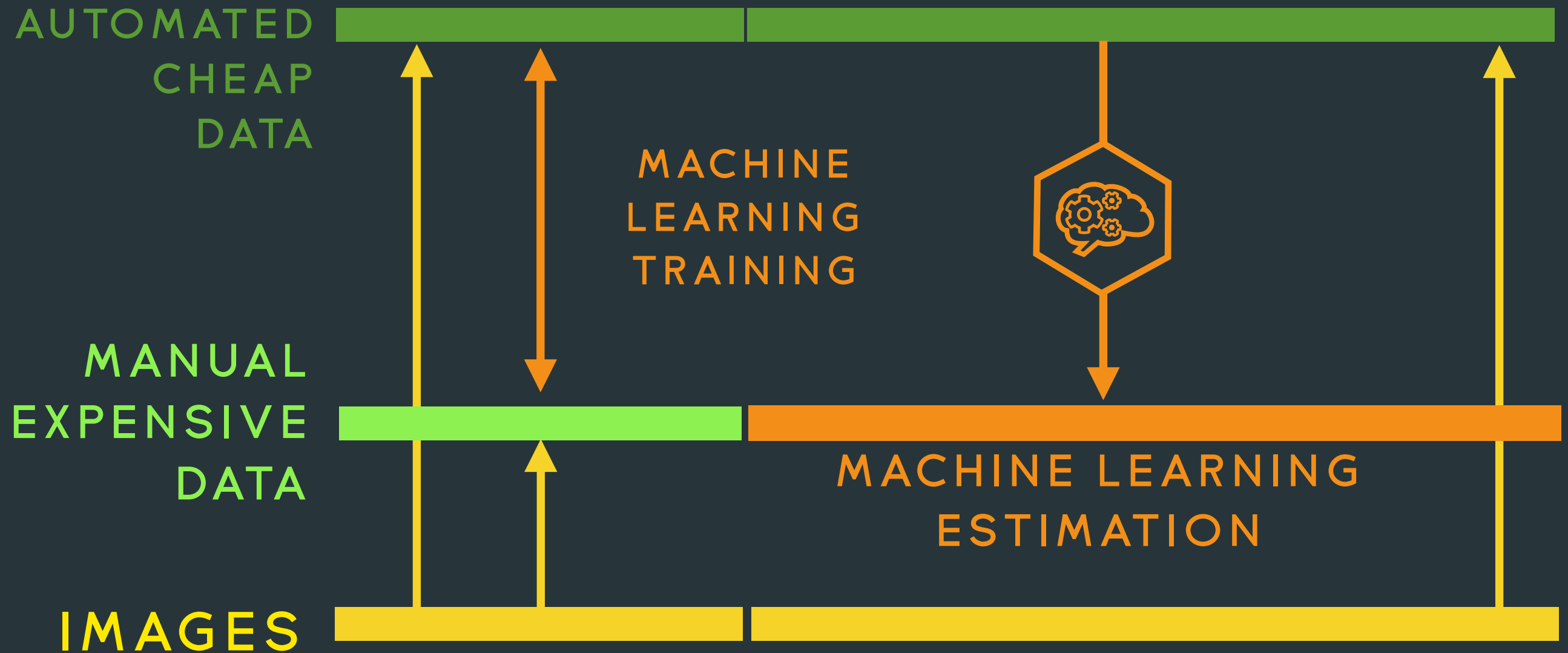
MACHINE LEARNING ASSISTED ANALYSIS



MACHINE LEARNING ASSISTED ANALYSIS

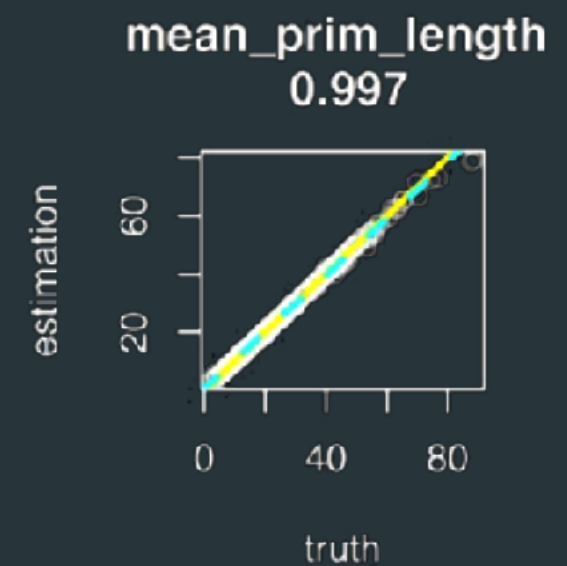
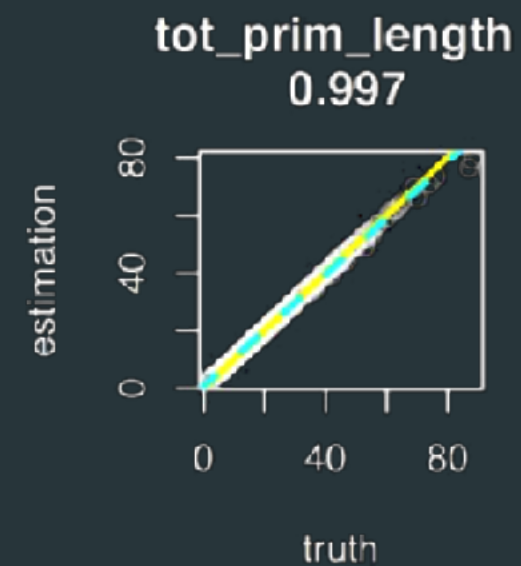
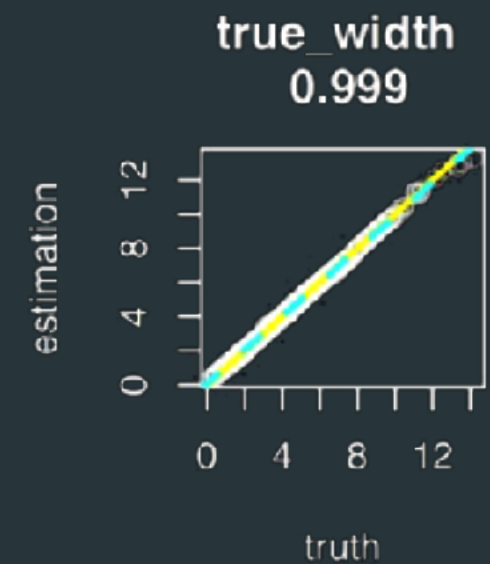
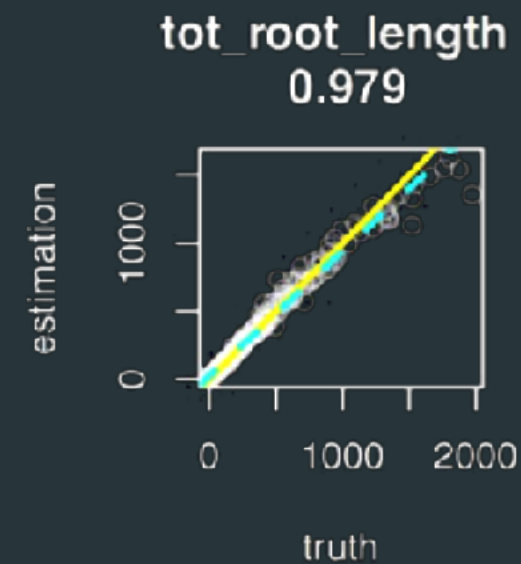


MACHINE LEARNING ASSISTED ANALYSIS



SYNTHETIC DATA

IMAGEJ MACRO	IMAGEJ MACRO
GROUND-TRUTH	MACHINE LEARNING ESTIMATION
5000 IMAGES	5000 IMAGES



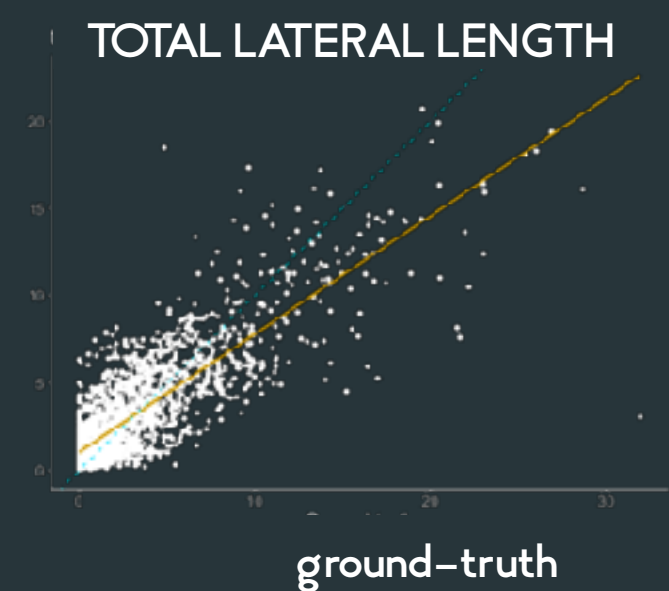
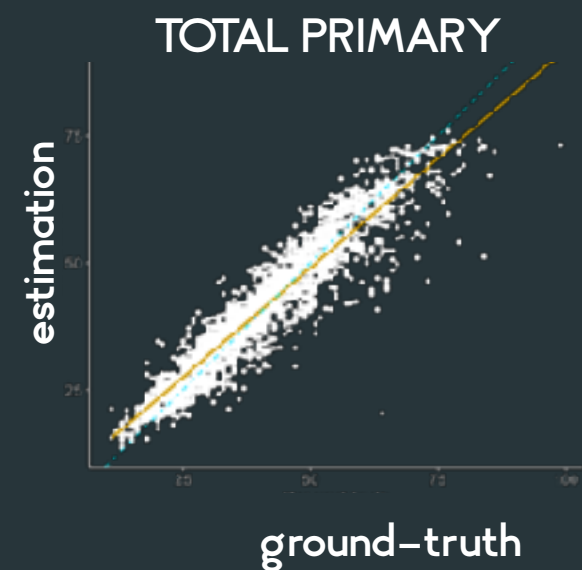
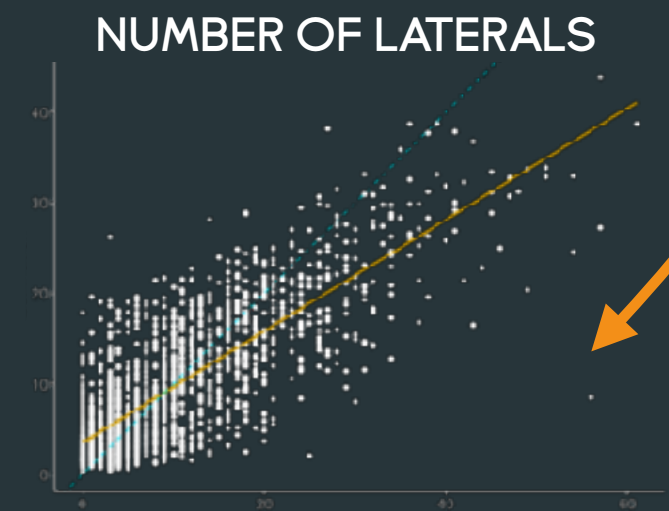
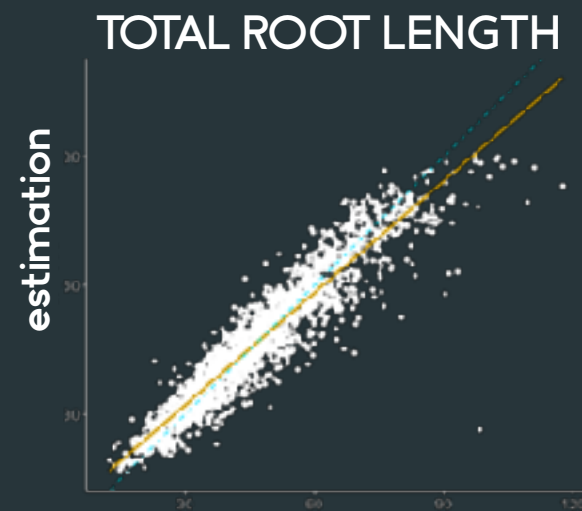
Manuel Noll



Iko Koevoets
[@IkoKoevoets](#)

WHEAT ROOT SYSTEM ARCHITECTURE

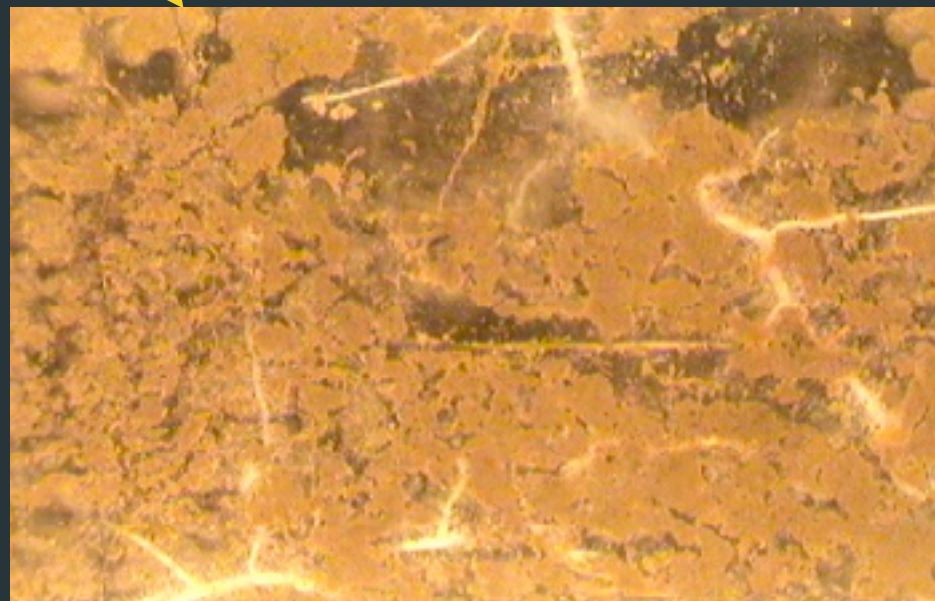
IMAGEJ MACRO	IMAGEJ MACRO
ROOTNAV	MACHINE LEARNING ESTIMATION
500 IMAGES	2000 IMAGES



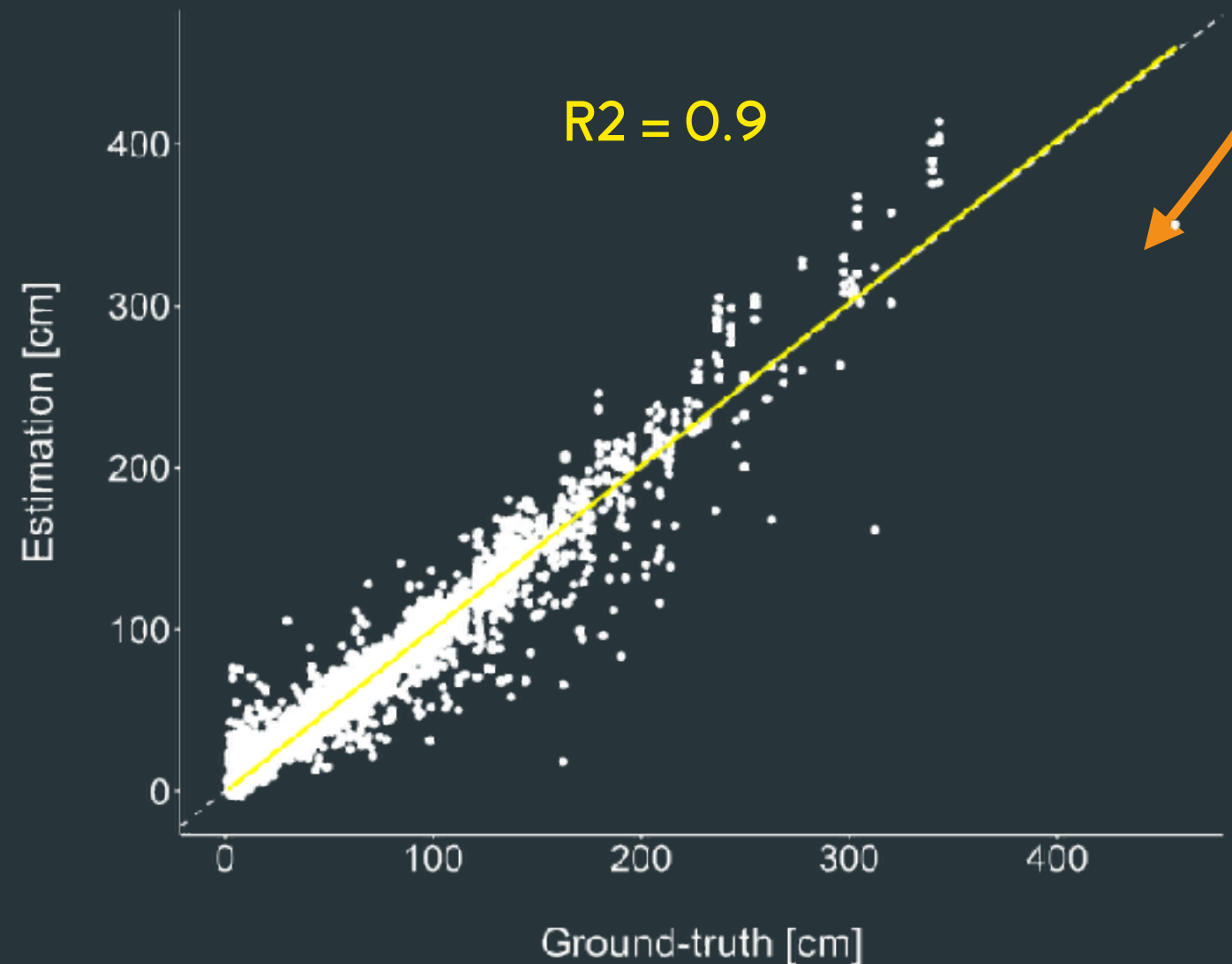
Jonathan Atkinson
@Jon_AAtkinson

MINI RHIZOTRON IMAGES

IMAGEJ MACRO	IMAGEJ MACRO
ROOTFLY	MACHINE LEARNING ESTIMATION
8000 IMAGES	1 000 IMAGES



TOTAL ROOT LENGTH

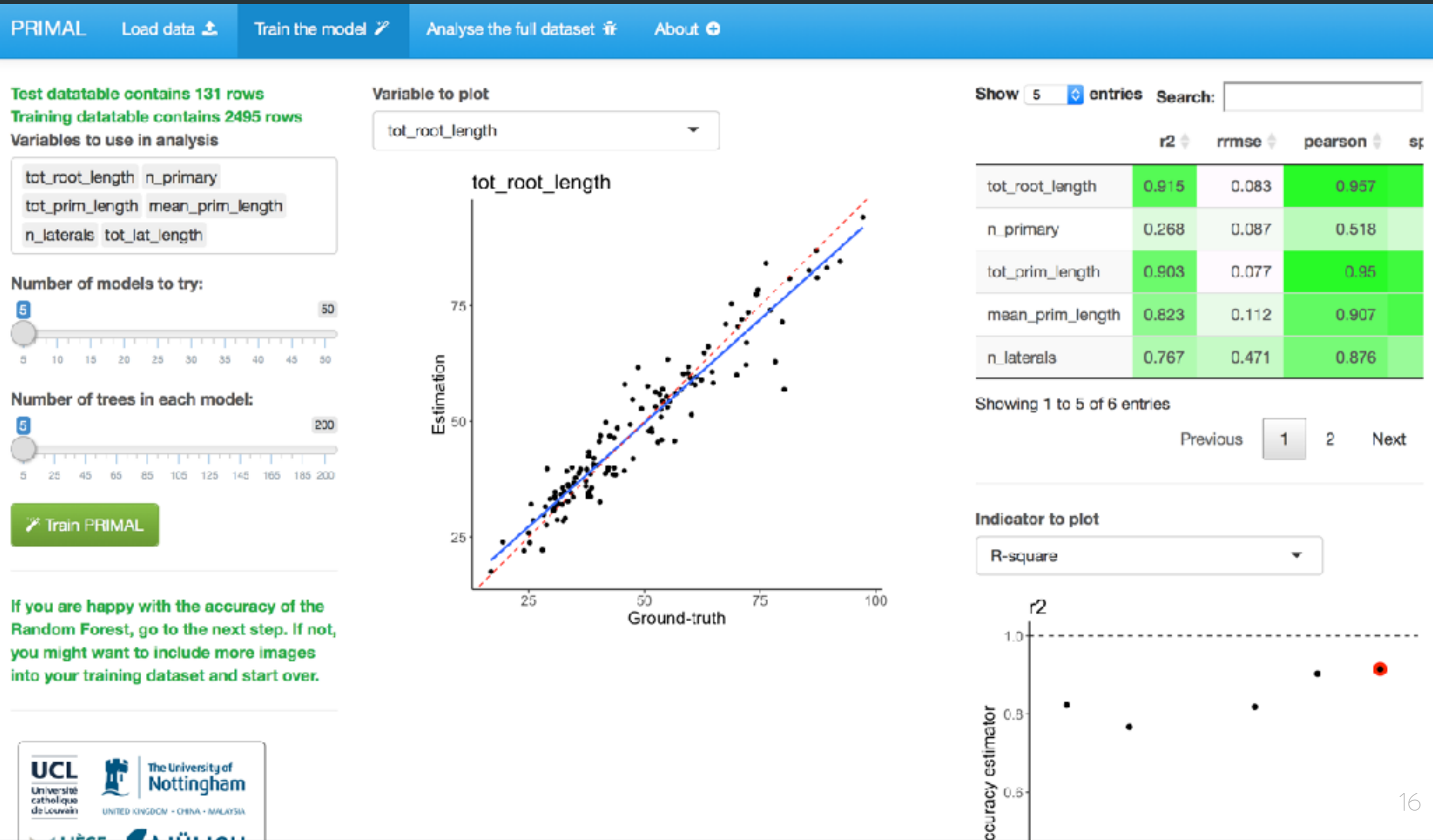


Shehan Morandage



Mirjam Zorner

R SHINY APP



<https://plantmodelling.github.io/primal/>

IMAGE
ANALYSIS

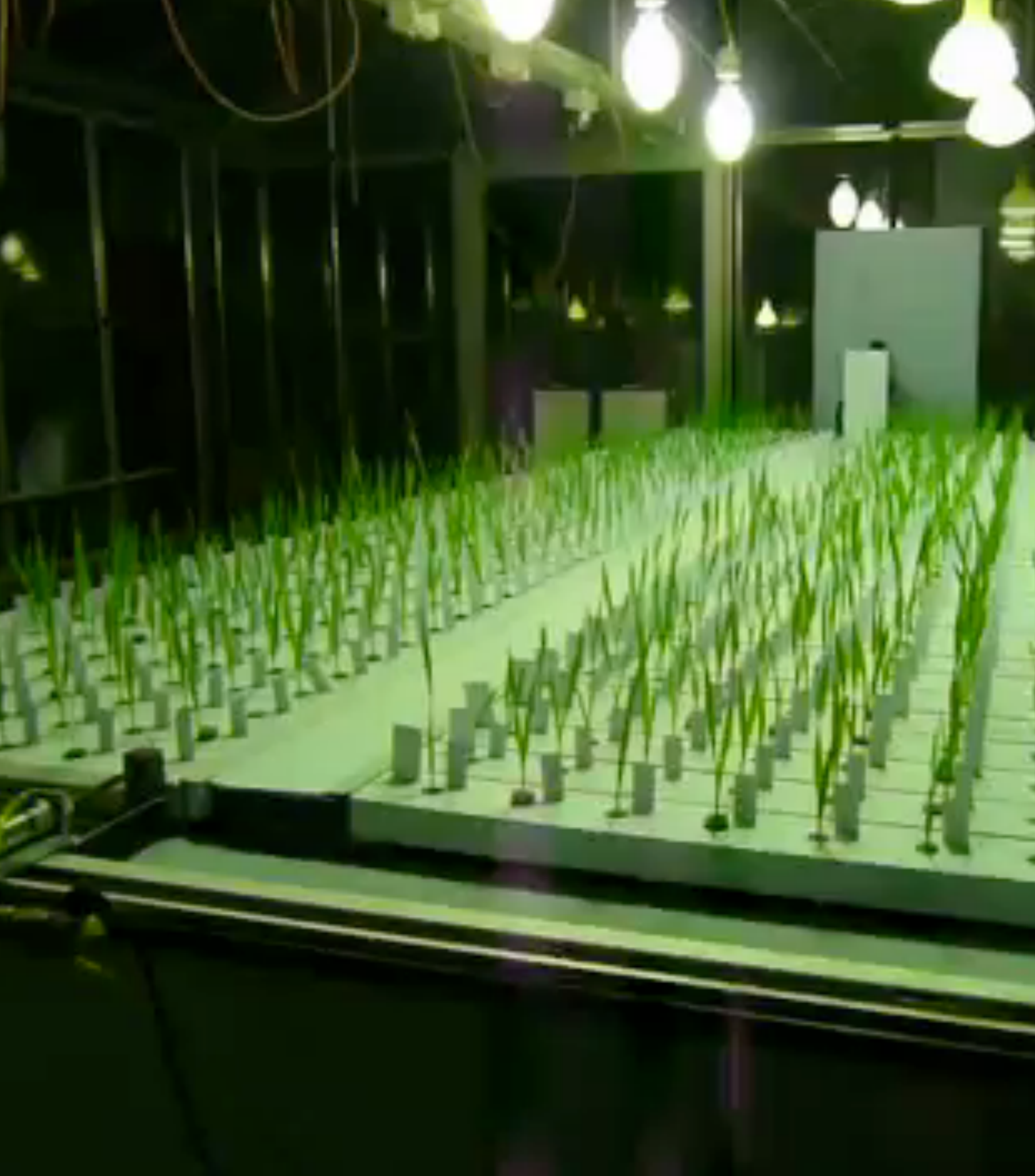


ROOT
MODELS

3



MACHINE
LEARNING



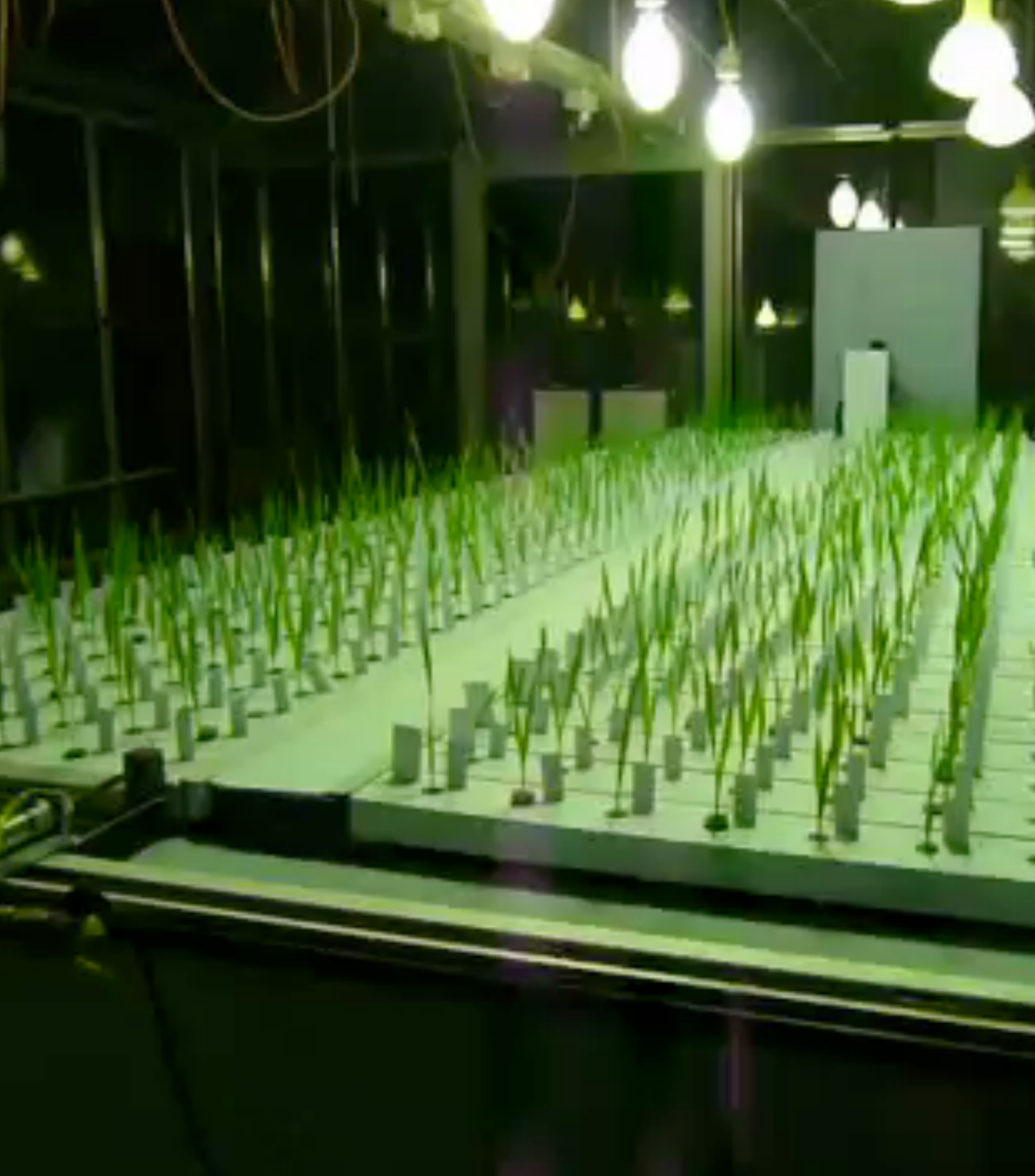
AEROPONIC PHENOTYPING PLATFORM

1000 PLANTS

1 IMAGE / PLANT / 2H

ROOT + SHOOT

240 000 IMAGES



AEROPONIC PHENOTYPING PLATFORM

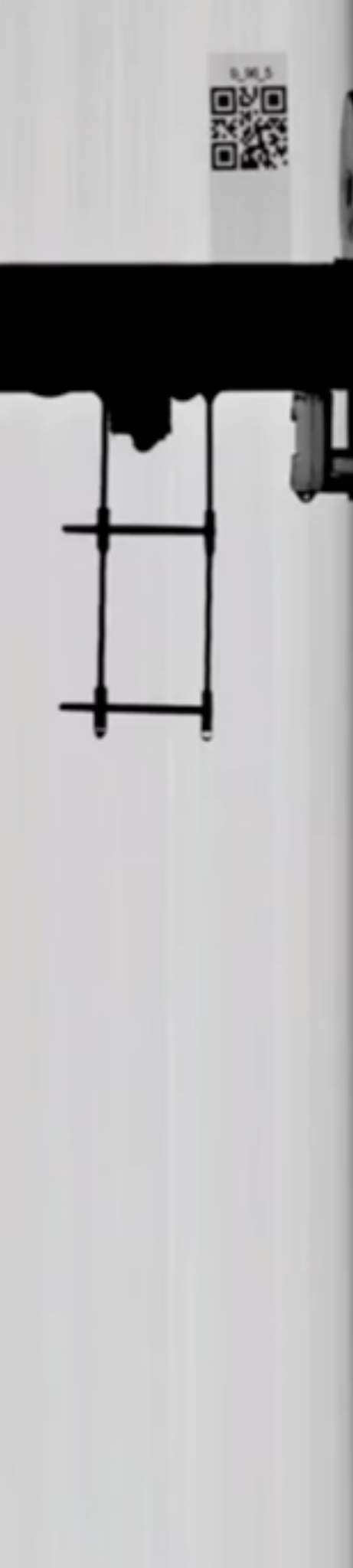
1000 PLANTS

1 IMAGE / PLANT / 2H

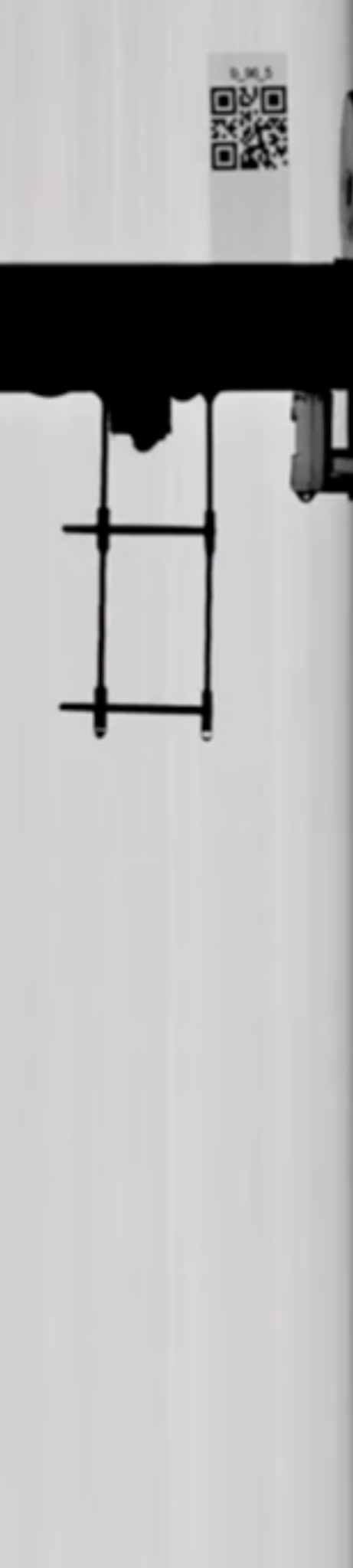
ROOT + SHOOT

240 000 IMAGES

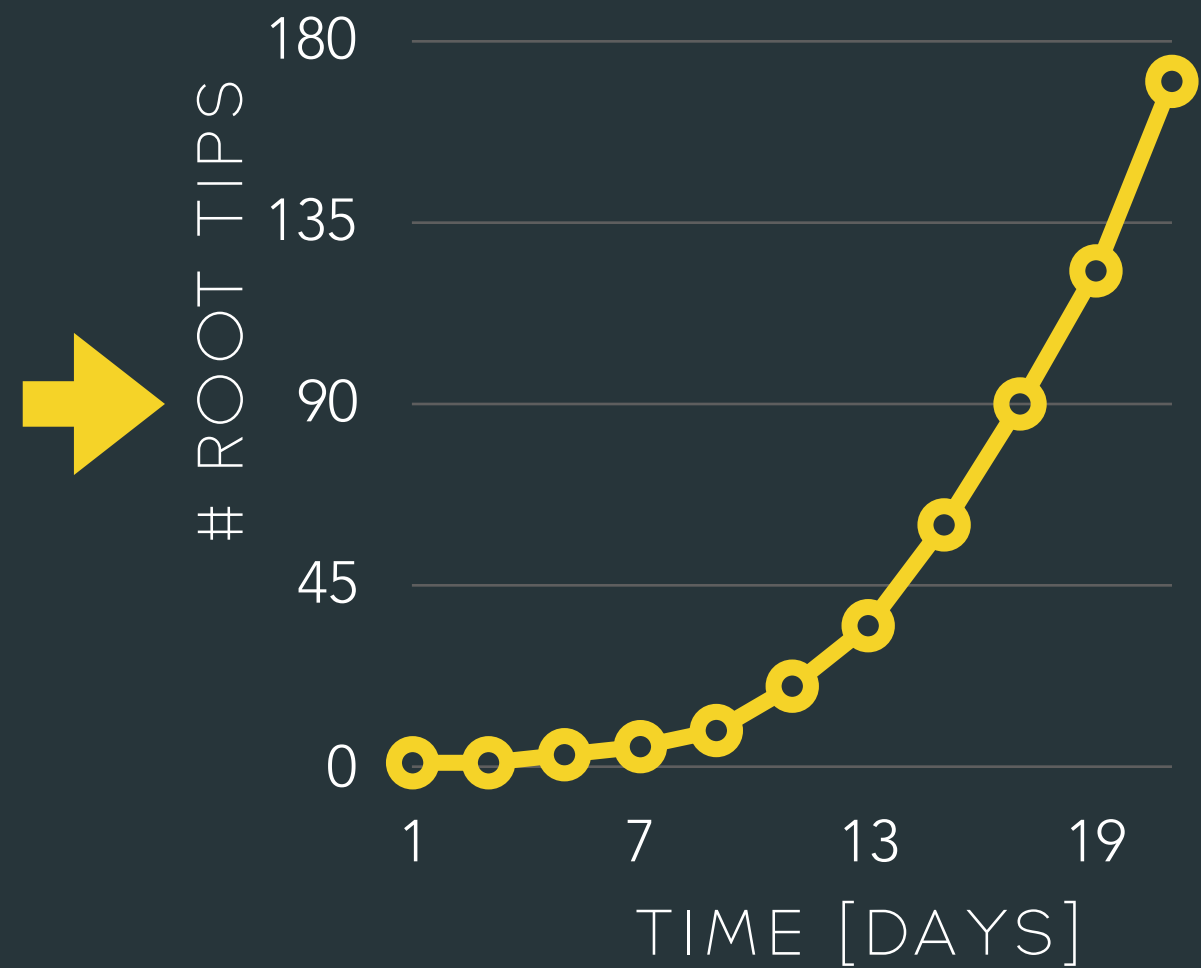
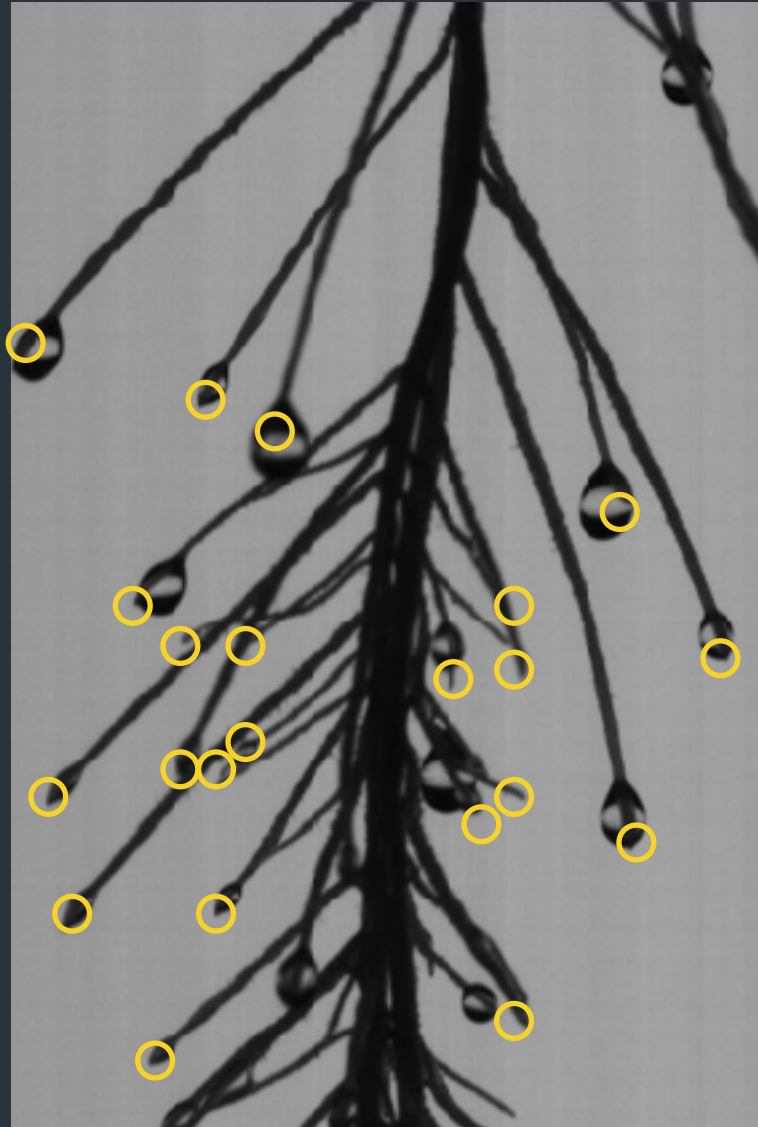
AUTOMATED TIP DETECTION



AUTOMATED TIP DETECTION

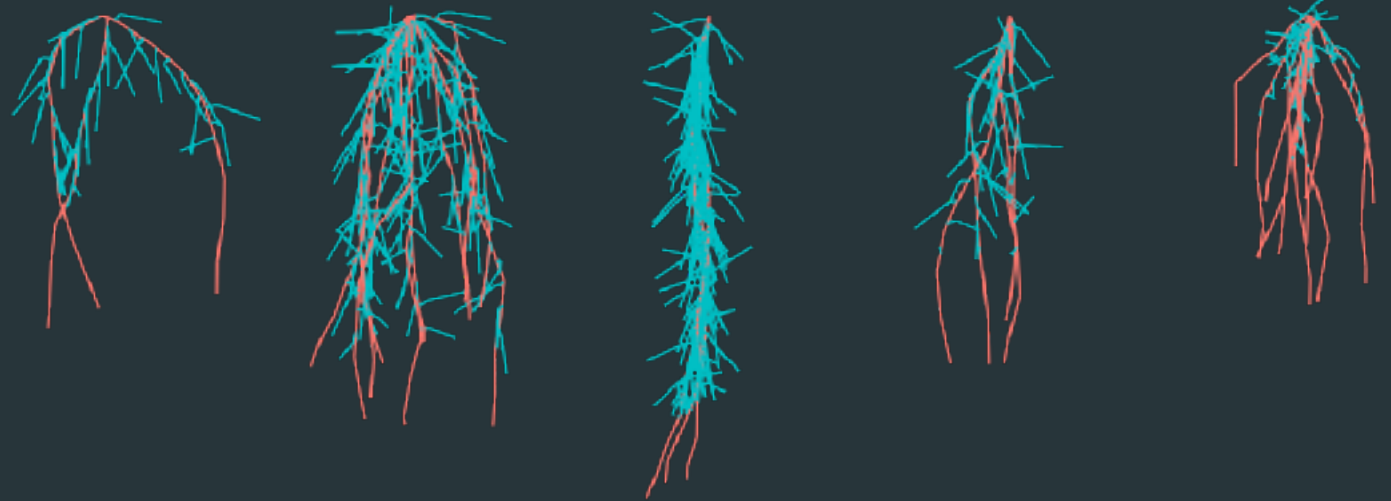


AUTOMATED TIP DETECTION



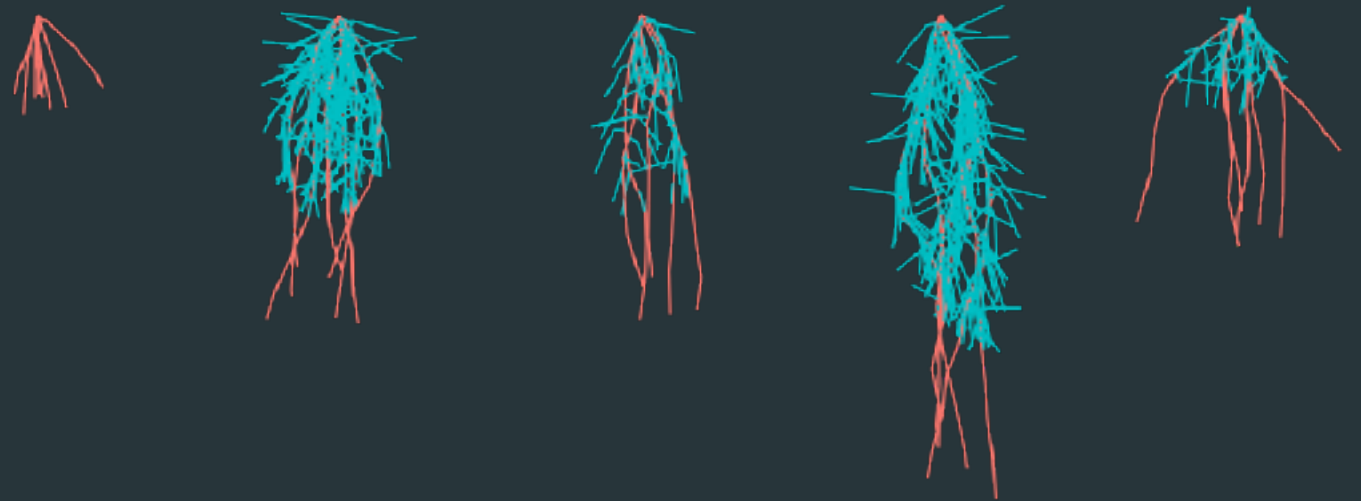
USING **CROOTBOX** TO CREATE A CUSTOM SYNTHETIC LIBRARY

1. DEFINE BASE
PARAMETER SET

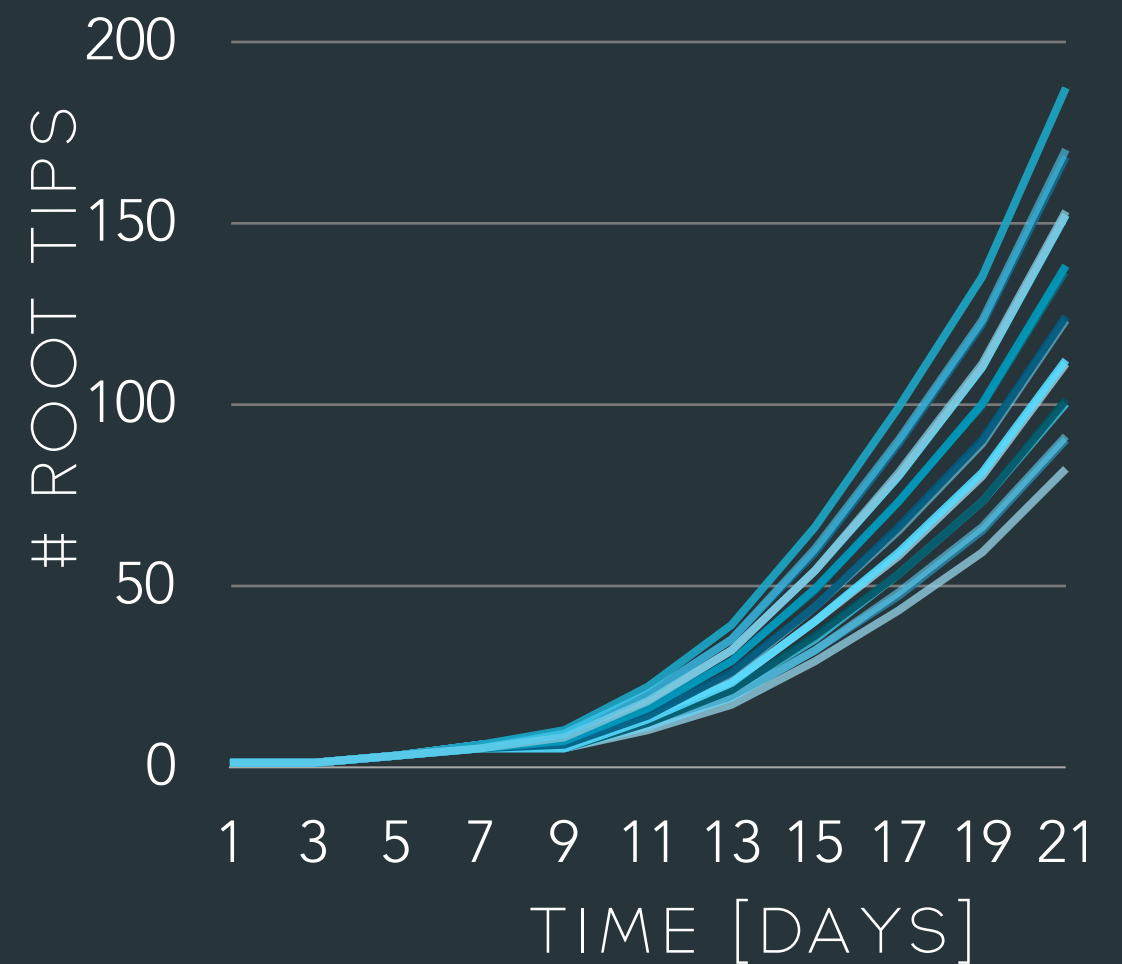
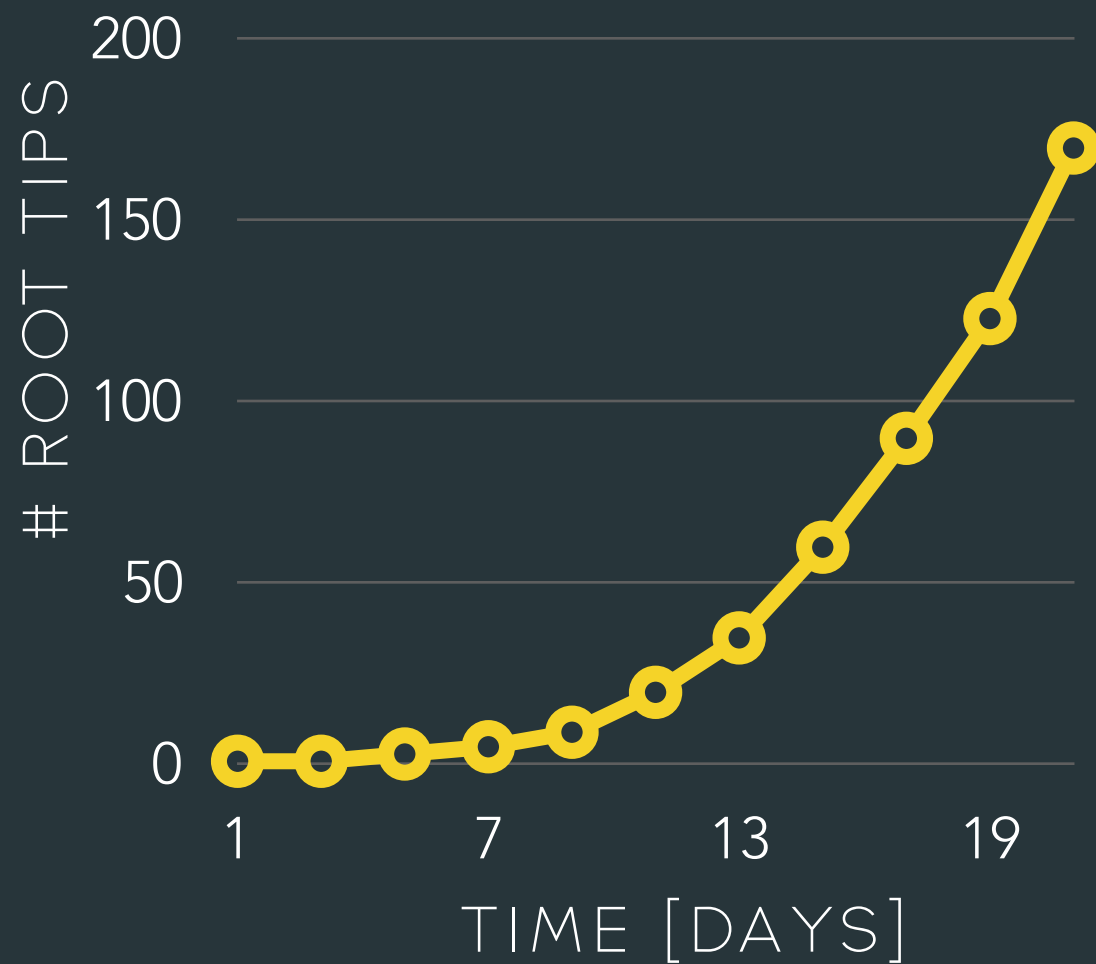


2. RUN MODEL
WITH DEVIATIONS

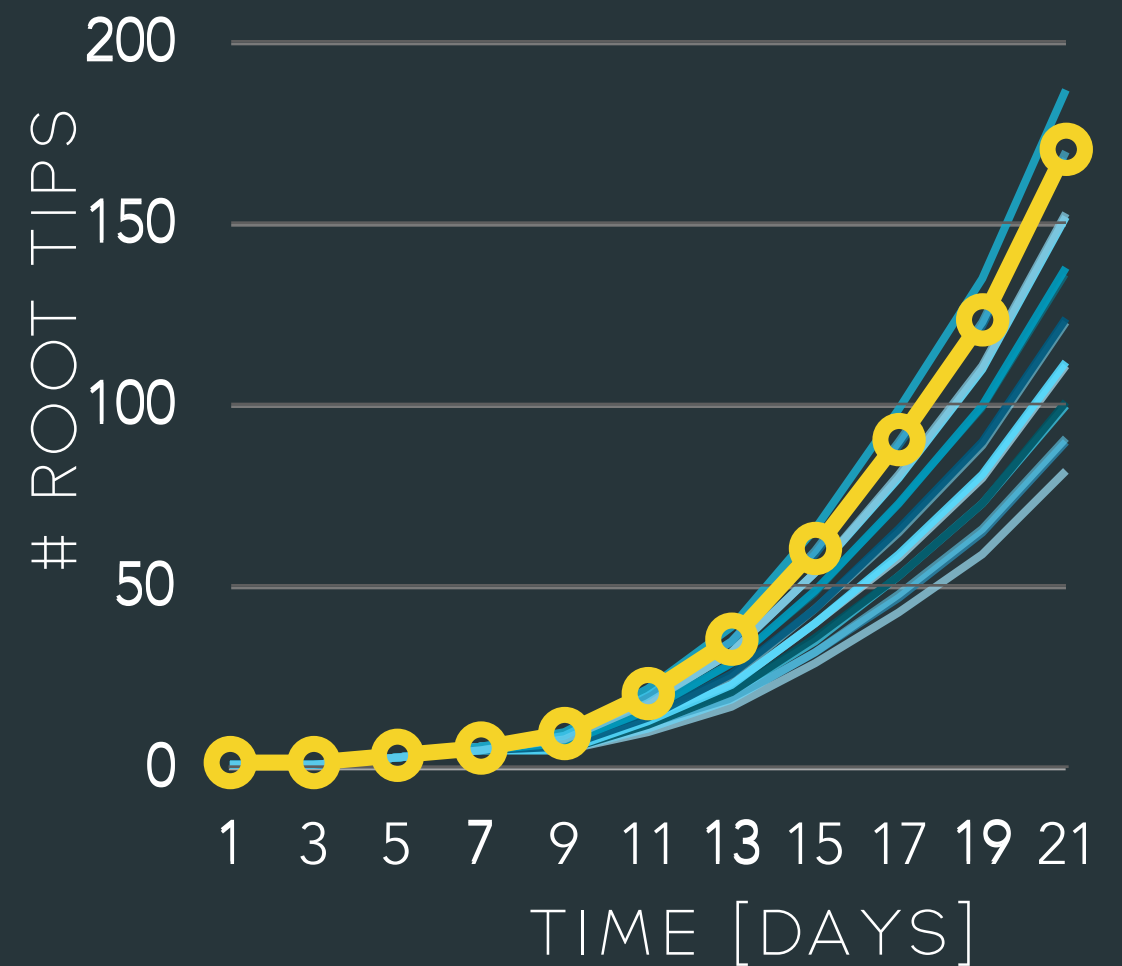
3. STORE PARAMETERS
AND RSMLS



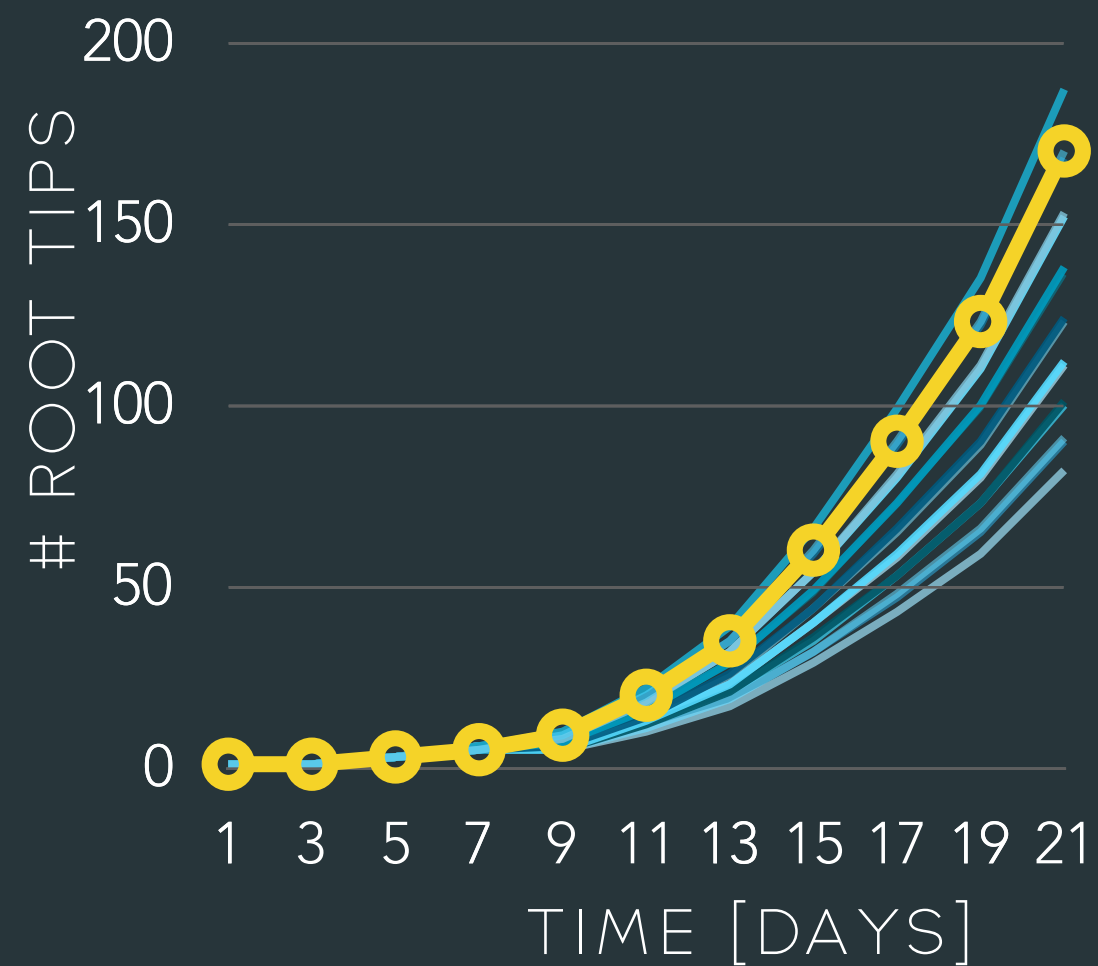
FITTING EXPERIMENTS TO MODELS



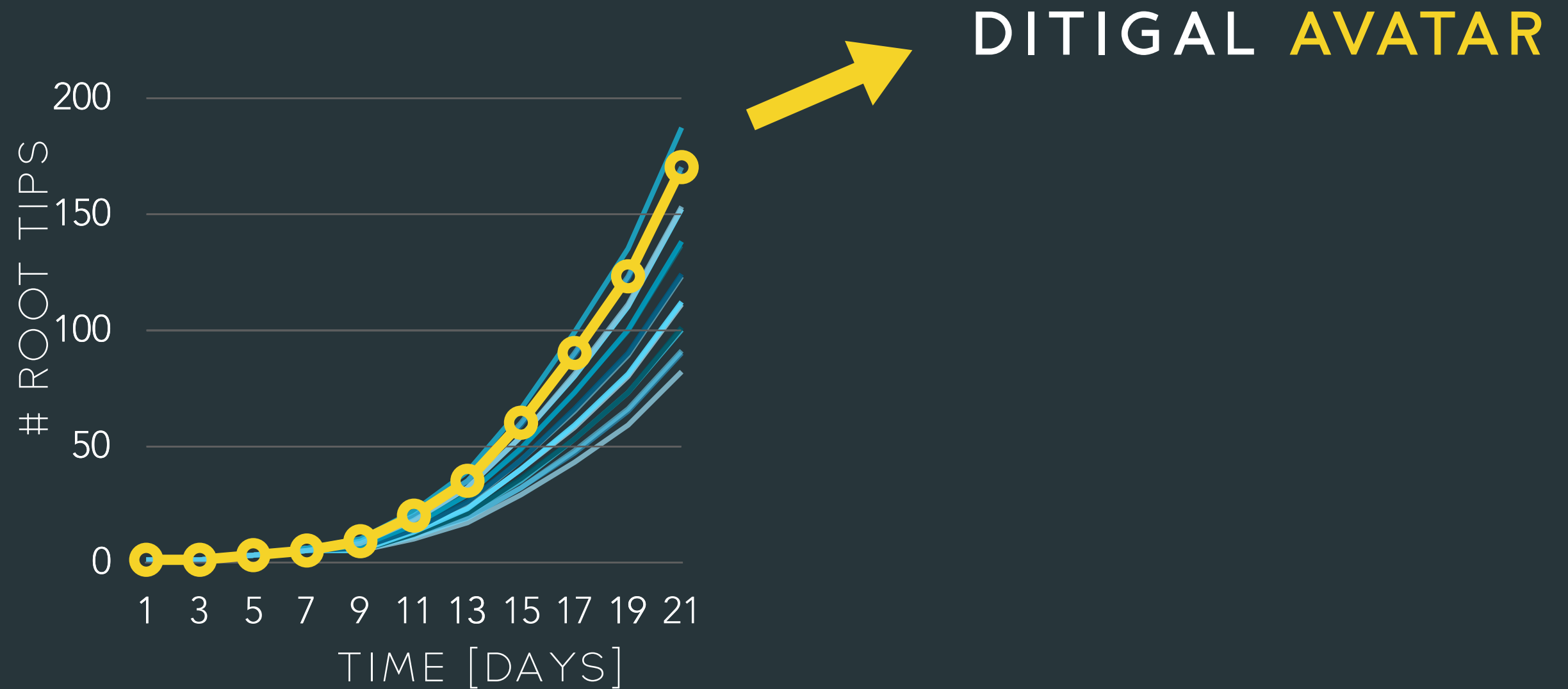
FITTING EXPERIMENTS TO MODELS



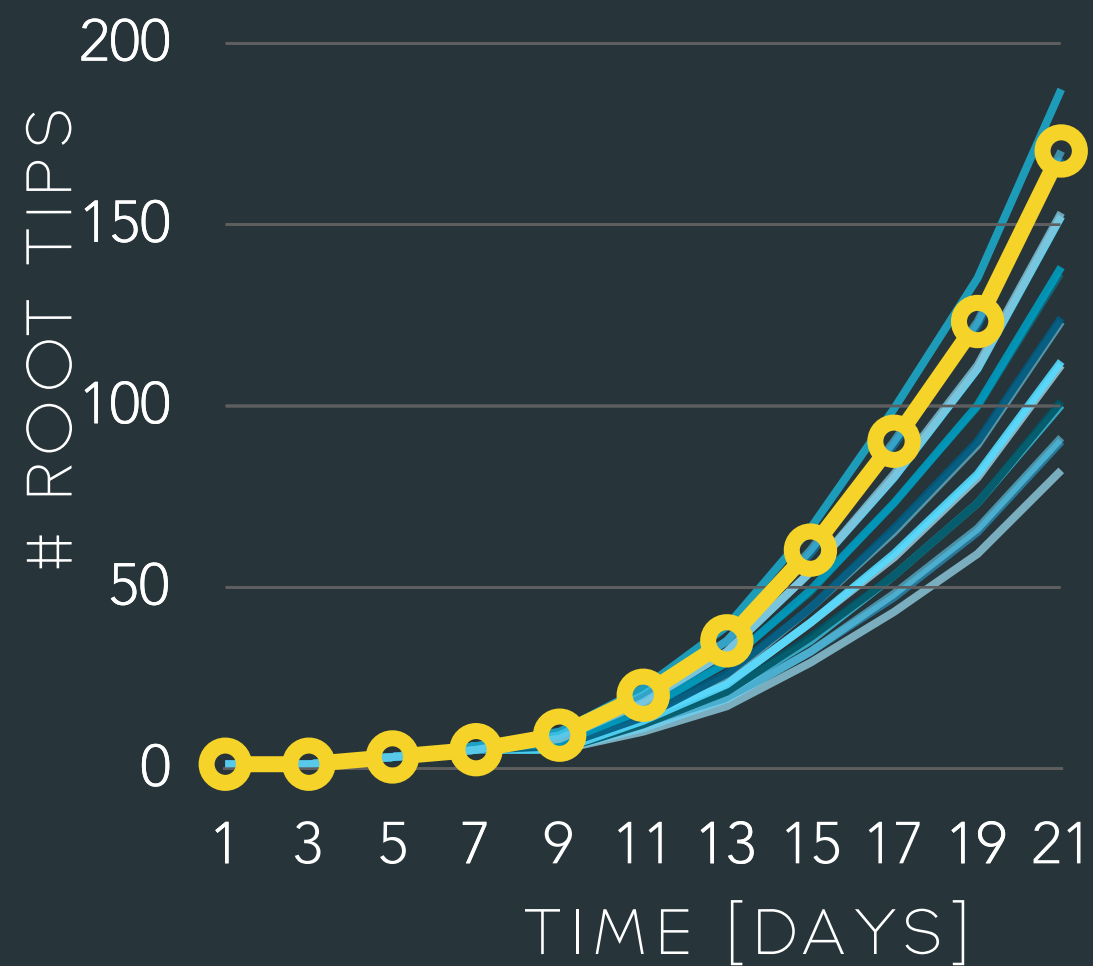
FITTING EXPERIMENTS TO MODELS



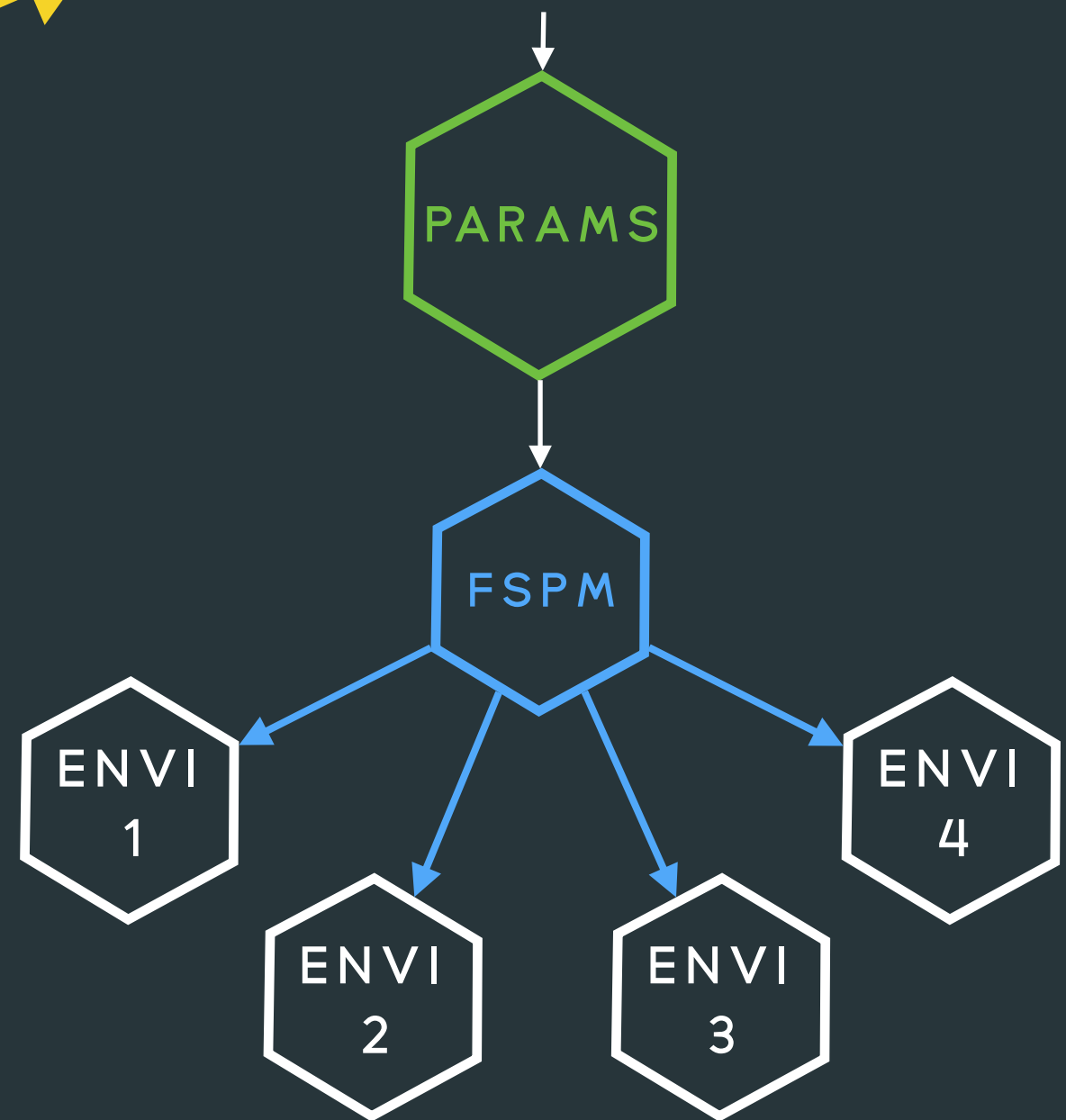
FITTING EXPERIMENTS TO MODELS

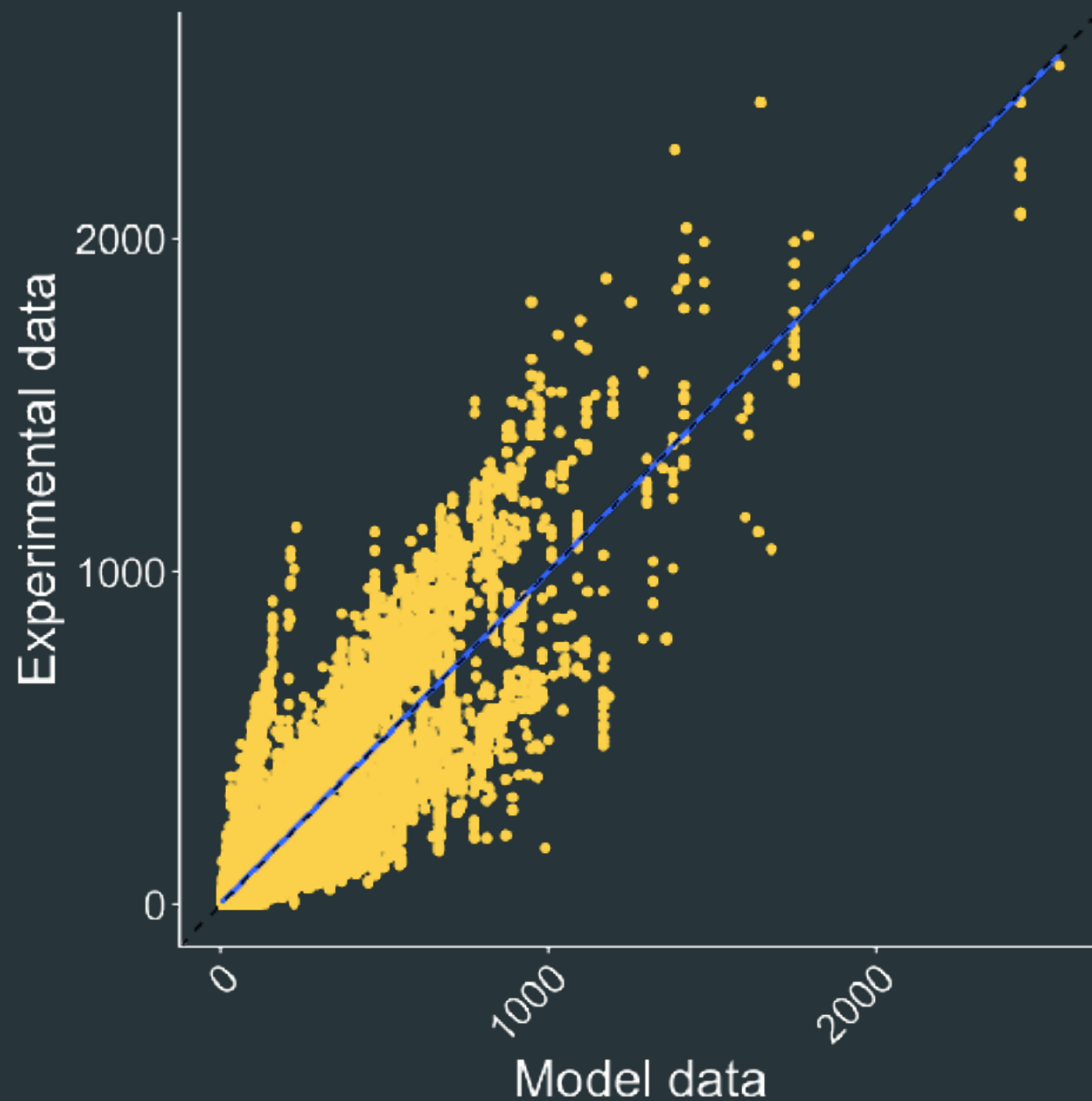


FITTING EXPERIMENTS TO MODELS



DITIGAL AVATAR





GOOD FIT
BETWEEN
EXPERIMENTAL
AND
MODELLED DATA

1000 PLANTS

MEAN **$R^2 > 0.9$**



WORK
IN
PROGRESS

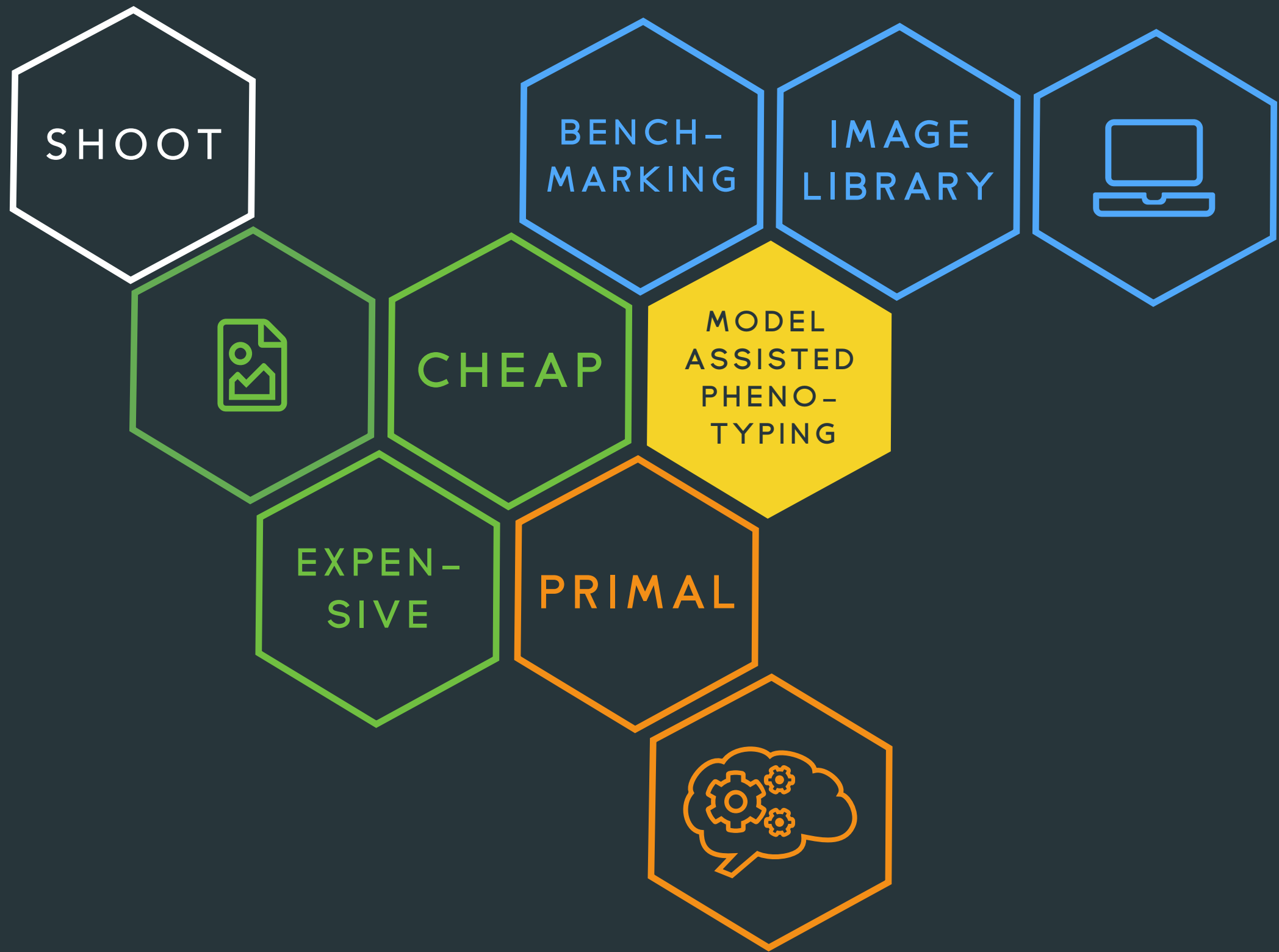






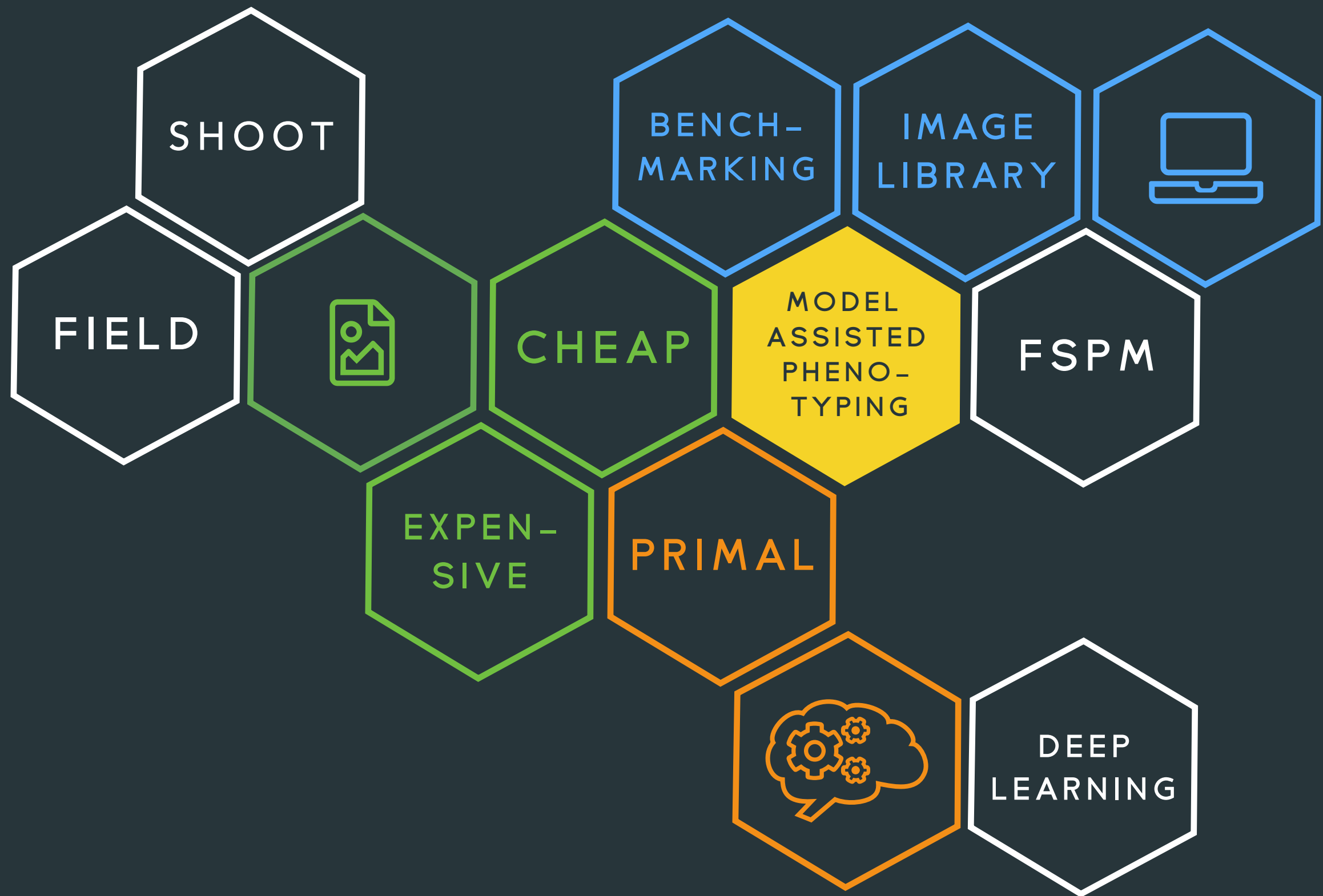














THE FUTURE IS
TO COMBINE
IMAGE ANALYSIS,
MODELLING AND
MACHINE LEARNING

THANK YOU ANY QUESTIONS ?



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LA LIBERTÉ DE CHERCHER

 **JÜLICH**
Forschungszentrum

Presentation available on **figshare**

bit.ly/lobet-phenome