
Richard J Morris
Opportunities for AI in Plant Biology and Crop Research

1

2

"If I can't compute it, I don't understand it."

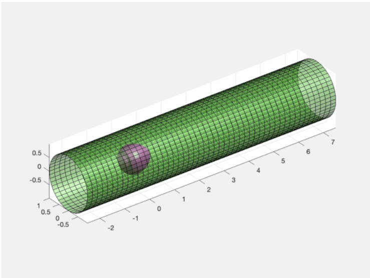
–*John von Neumann*

3

Mechanistic models build on previous knowledge and have meaningful parameters

4

Fluid dynamics simulations of fluid flow in the xylem

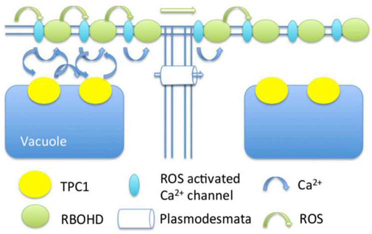


Evans and Morris (2016) The Plant Journal

Blyth and Morris (2018) Mathematical Modelling in Plant Biology

Blyth and Morris (2019) Frontiers in Plant Science

Fire-diffuse-fire modelling of spatio-temporal calcium waves

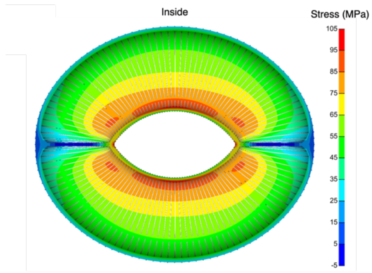


Evans et al. (2016) Plant Physiology

Capoen et al (2011) PNAS

Vaz Martins et al (2016) BMC Systems Biology

Finite Element Method modelling of guard cell dynamics

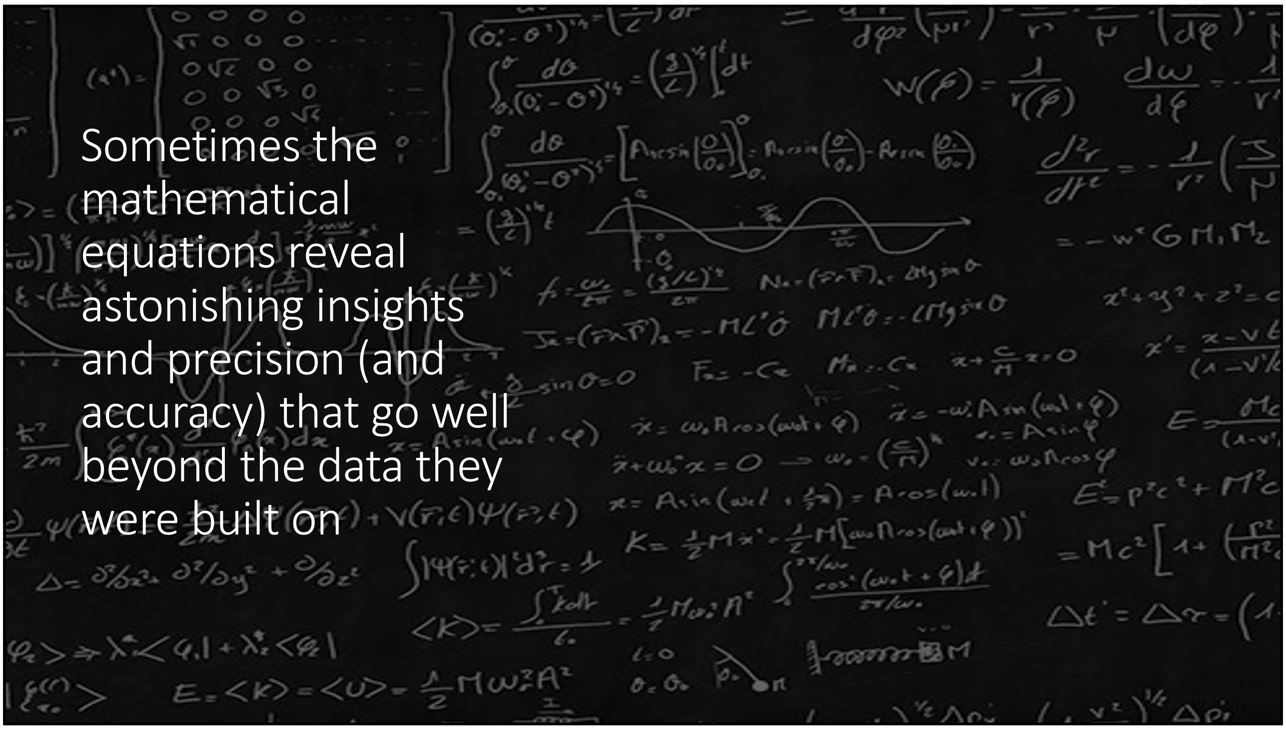


Woolfenden et al. (2017) The Plant Journal

Carter et al. (2017) Current Biology

Woolfenden et al. (2018) Trends in Plant Science

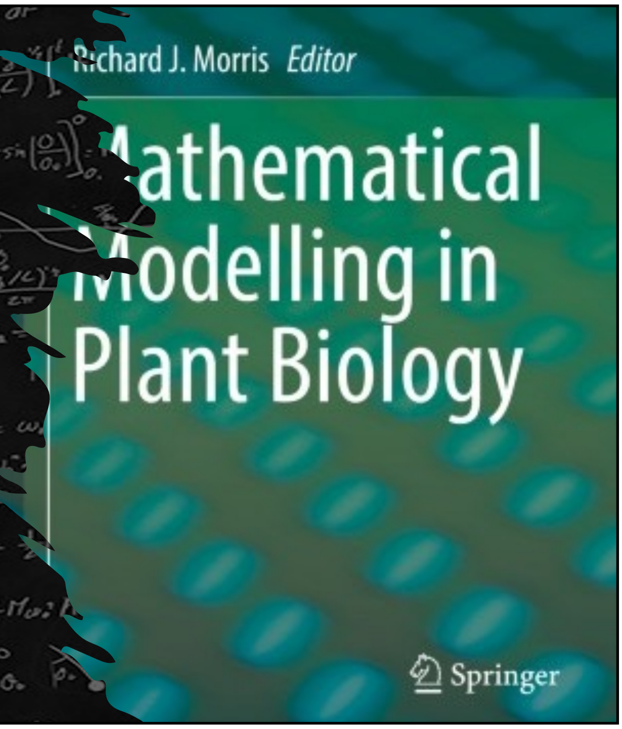
5



Sometimes the mathematical equations reveal astonishing insights and precision (and accuracy) that go well beyond the data they were built on

6

Sometimes the mathematical equations reveal astonishing insights and precision (and accuracy) that go well beyond the data they were built on

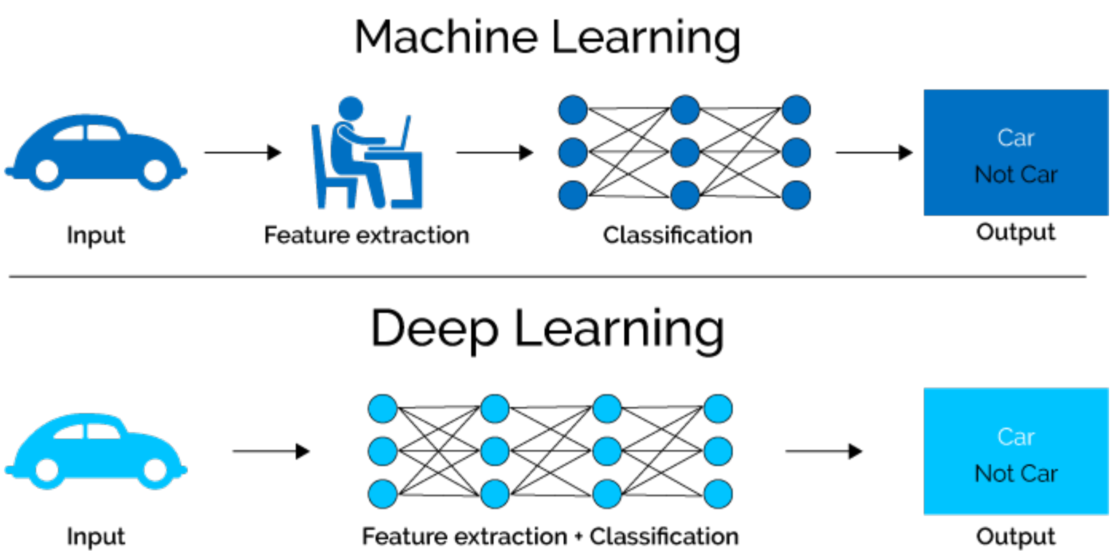


7

So, what's all the fuss about deep learning?

8

9



https://www.quora.com/What-is-the-difference-between-deep-learning-and-usual-machine-learning

10

The few extra layers are game changing!

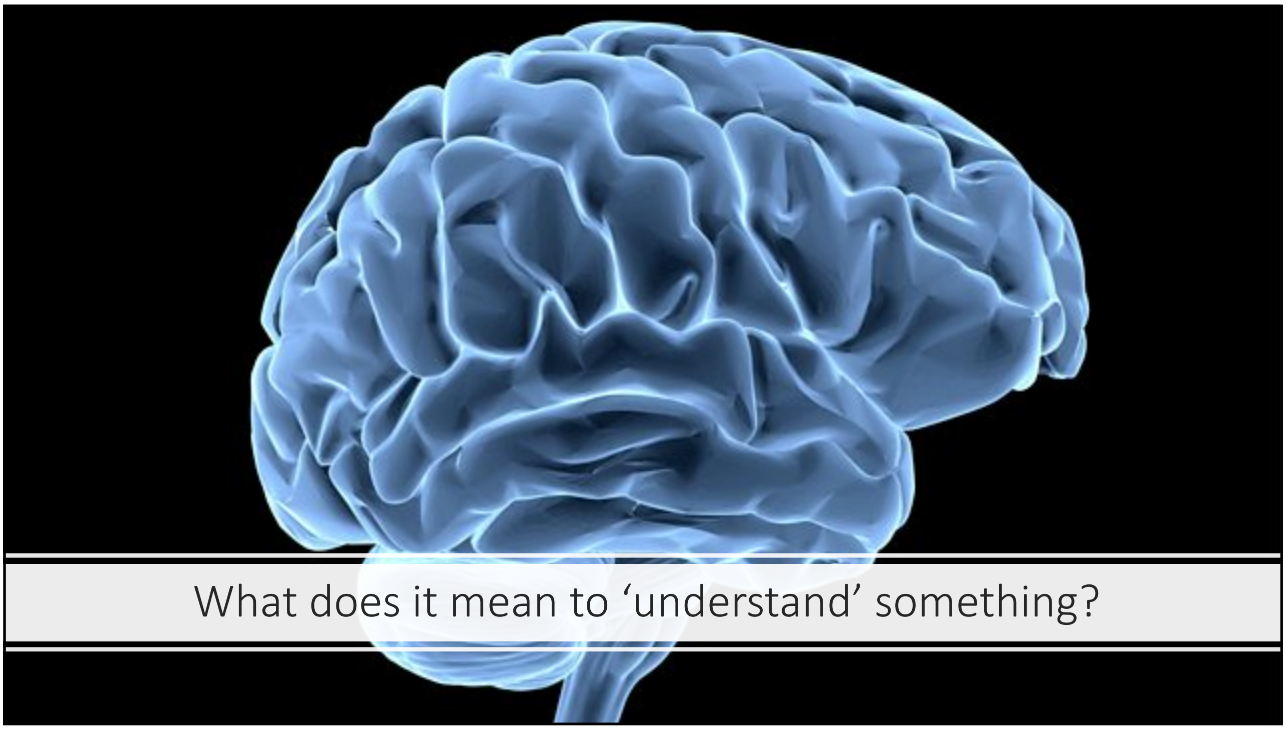
- Breaks the 80:20 rule for feature selection:training
- No longer requires expert domain knowledge
- Computer scientists are taking over

11

Deep learning approaches are not restricted by the imagination of the modeller but are currently difficult to 'understand'

12

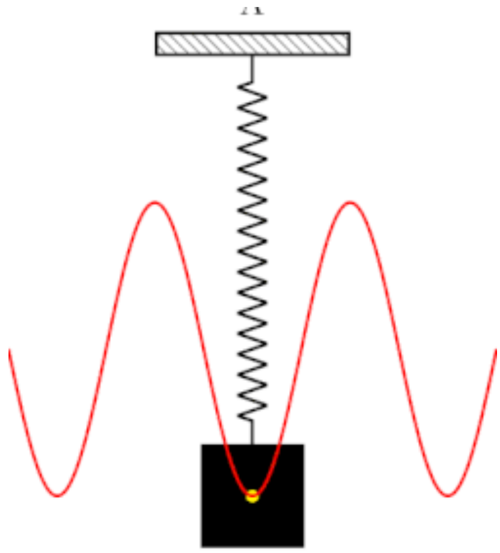
13



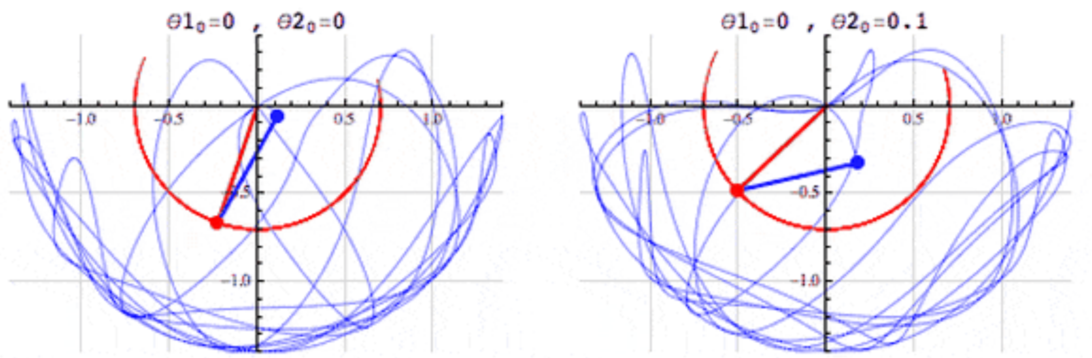
What does it mean to ‘understand’ something?

14

To ‘understand’ often means relating it to something else



15



Even simple systems can show non-intuitive behaviour

16

"I think I can safely say that nobody really understands quantum mechanics."

–*Richard Feynman*

17

AI for plant disease detection in wheat

18

From lab to field – getting real world data

19

From lab to field – getting real world data

What?

Images of diseased (Septoria, yellow rust, brown rust, mildew) and healthy wheat leaves

Where?

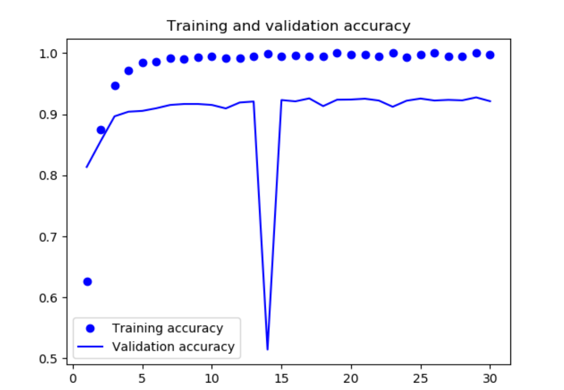
Multiple sites across the UK, in England, Ireland and Scotland.

How?

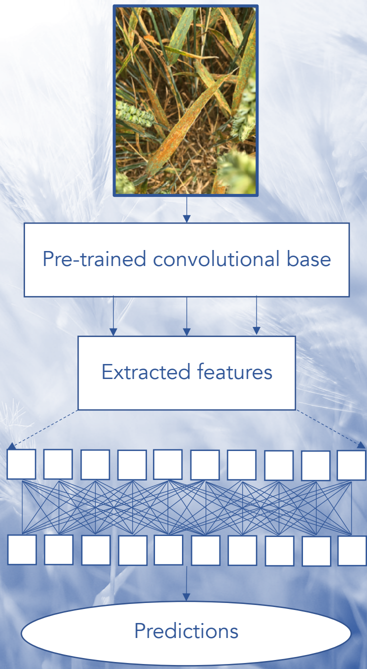
Predominantly using smartphone cameras, some with a digital camera
With all possible conditions

20

Networks – Pre-trained

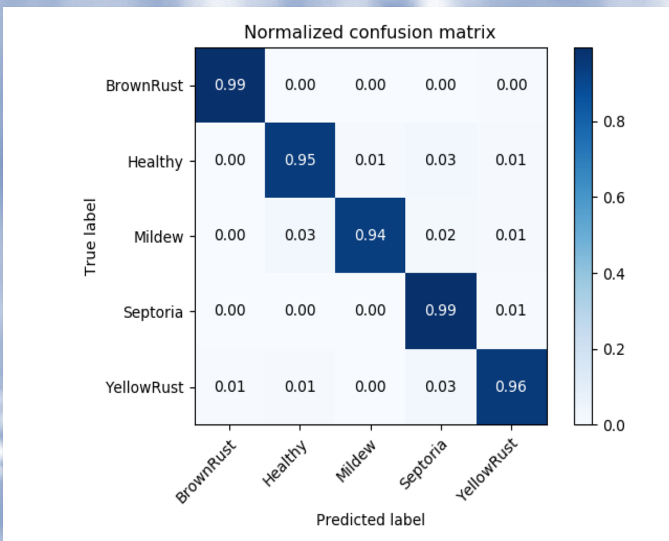


MobileNet (by Google) – Test accuracy 91.4%



21

Megan's network performs astonishingly well



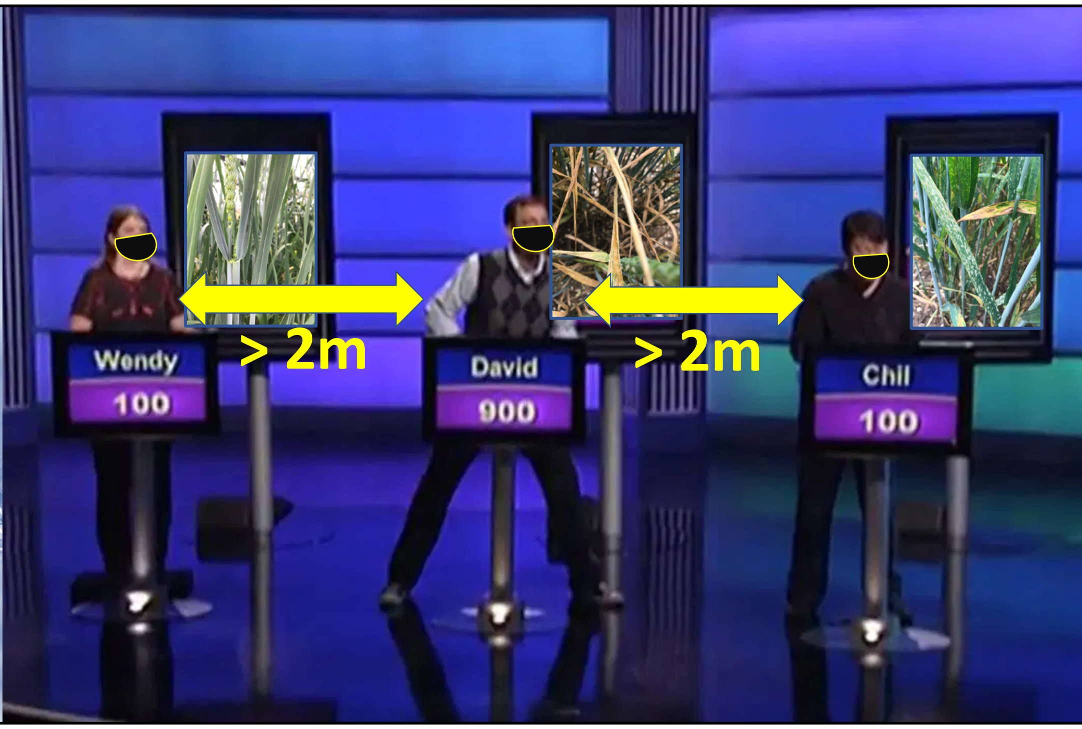
22


Test the Pathologist
THE
GAME SHOW
Experience

23


Wendy
100
David
900
Chil
100

24



25

Megan's network even outperforms expert crop pathologists!

	Participant 1		Participant 2		Participant 3		Participant 4		Participant 5		Network	
	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect	Correct	Incorrect
Brown rust	103	25	120	8	121	7	121	7	116	12	125	3
Healthy	104	18	98	24	94	28	96	26	117	5	99	23
Mildew	151	10	152	9	151	10	153	8	152	9	128	33
Septoria	265	84	273	76	296	53	331	18	266	83	336	13
Yellow rust	215	24	217	22	204	35	167	72	207	32	200	39
Accuracy	**83.88%**		**86.08%**		**86.68%**		**86.88%**		**85.88%**		**88.88%**	

26

Unravelling the control of developmental transitions in Brassicas

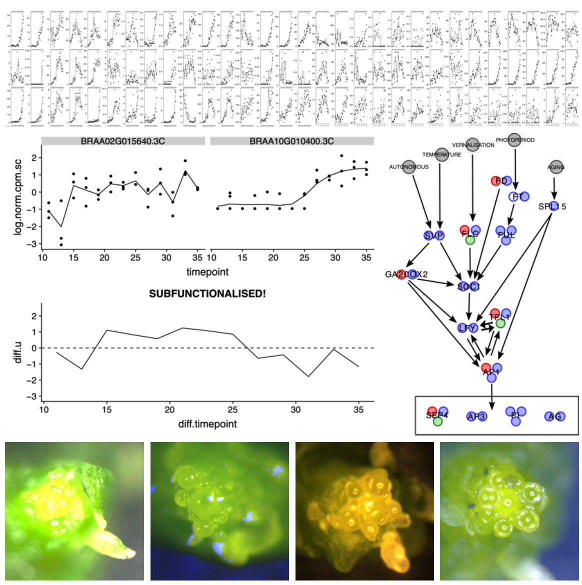
BRAVO
Brassica Rapeseed And Vegetable Optimisation

Alex Calderwood
Andrew Lloyd
Jo Hepworth
Eleri Tudor
Marc Jones
Shannon Woodhouse
Catherine Chinoy
Lorelie Bilham
Kevin Williams
Fiona Corke
John Doonan
Lars Ostergaard
Judith Irwin
Rachel Wells
Richard J Morris

UKRI Biotechnology and Biological Sciences Research Council

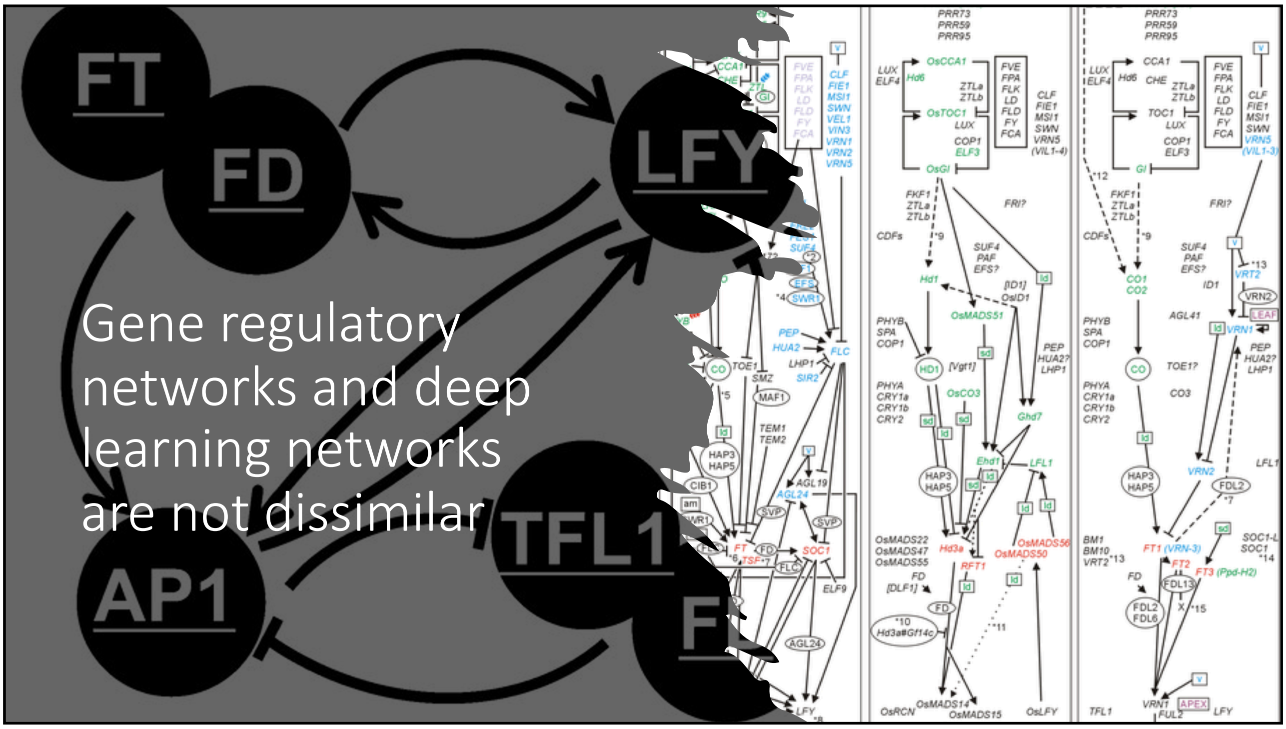
27

Using modelling and machine learning to unravel developmental transitions in Brassica



Calderwood et al. (2021) QPB (accepted)

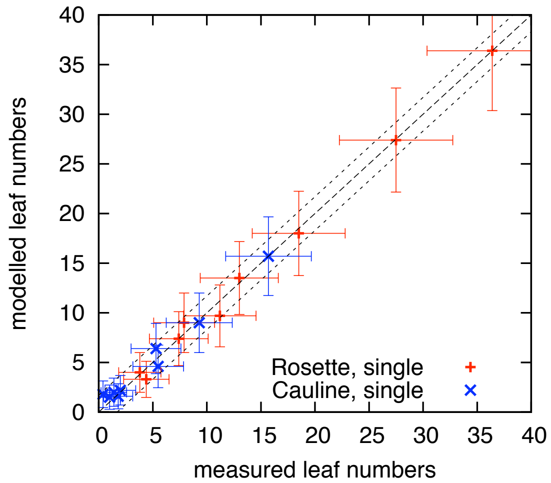
28



Gene regulatory networks and deep learning networks are not dissimilar

29

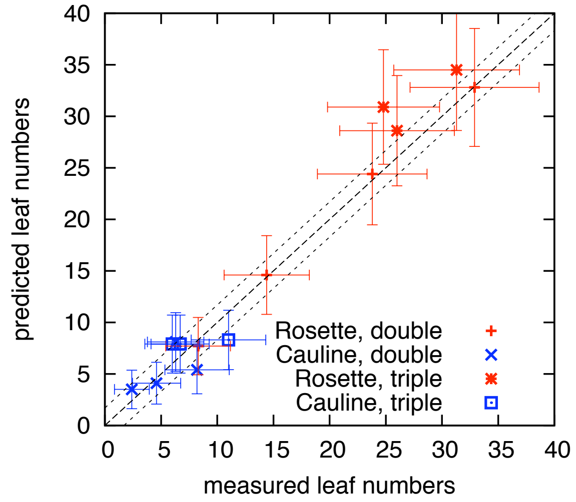
We can train gene regulatory networks for flowering time to predict leaf numbers



Jaeger et al. (2013) The Plant Cell

30

We can train gene regulatory networks for flowering time to predict leaf numbers

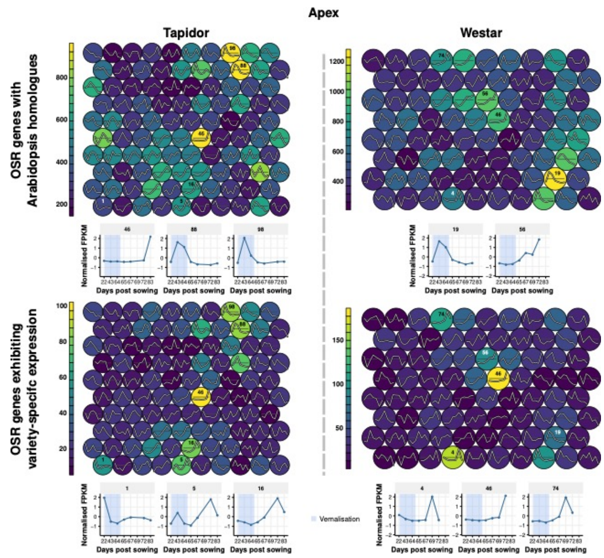


Jaeger et al. (2013) The Plant Cell

31

Self-organizing maps reveal patterns in transcript dynamics

Marc Jones



Jones et al. (2018) The Plant Journal

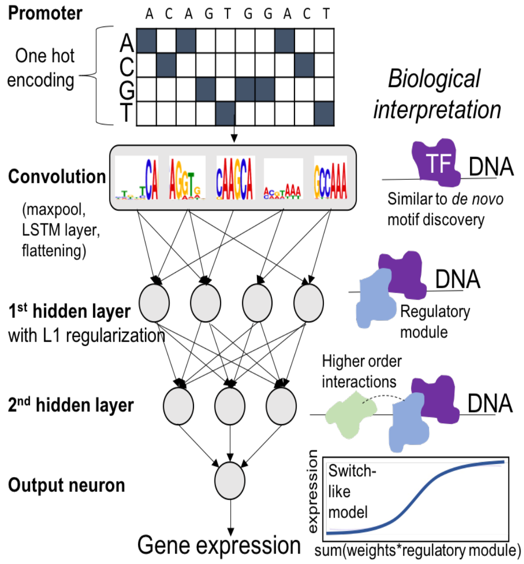
Jones et al. (2020) BMC Plant Biology

Jones et al. (2021) In preparation

32

Convolutional Neural Networks can predict expression in *Brassica rapa*

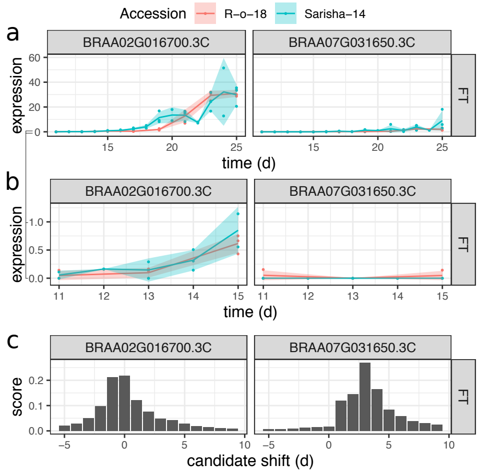
Daphne Ezer, York



33

Dynamic time warping of gene expression reveals key differences in flowering in *Brassica rapa*

Alex Calderwood

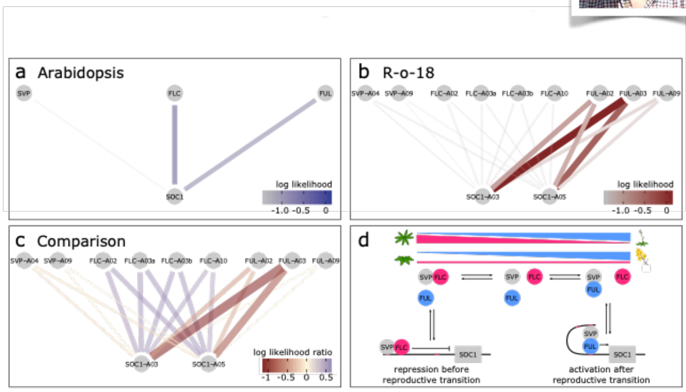


Calderwood et al. (2021) Quantitative Plant Biology

34

Gaussian Process network inference reveals key differences in flowering in *Brassica rapa*

Alex Calderwood

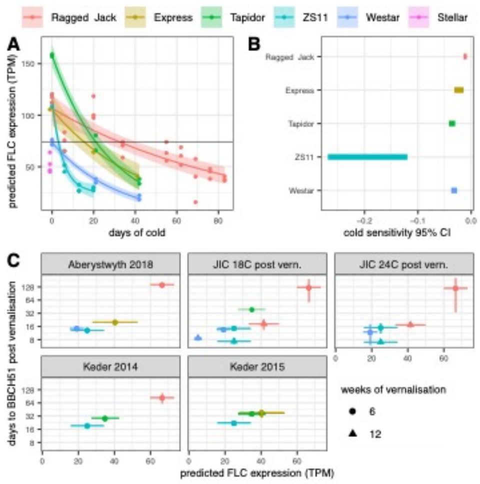


Calderwood et al. (2021) biorxiv

35

Unsupervised learning leads to a mathematical model that explains phenotypic diversity in *Brassica napus*

Alex Calderwood



Calderwood et al. (2021) New Phytologist

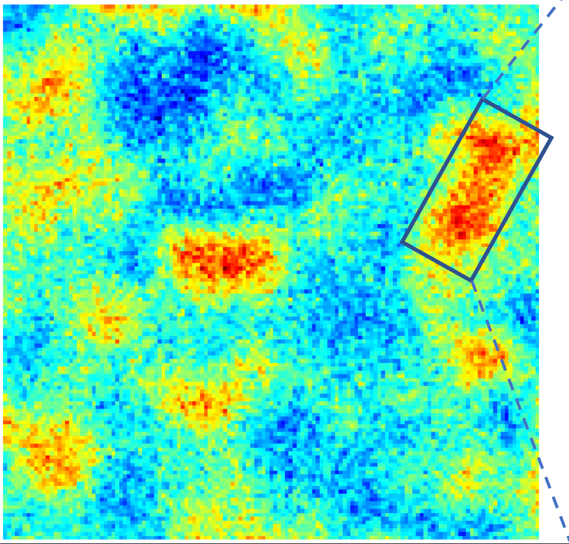
36

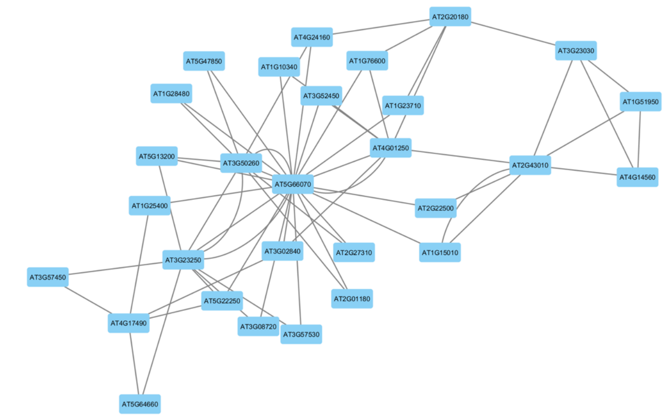
Trans-Learn – Multivariate Gene Patterns

KYOTO UNIVERSITY FOUNDED 1897 KYOTO JAPAN

Earlham Institute
Decoding Living Systems

71x71 gene matrix





The orange/red clusters found in a heatmap contain subsets of genes that collectively possess non-linear joint dependencies with the infection status/severity

37

National Plant PHENOMICS Centre

The Alan Turing Institute

From genotype to phenotype and back

38

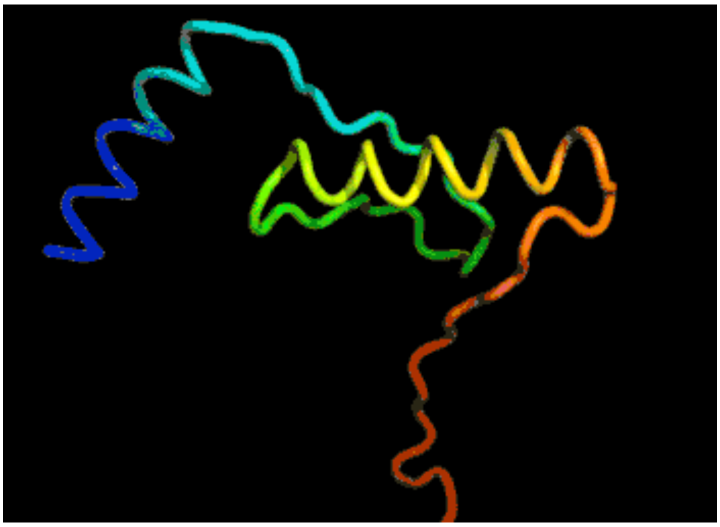
39

Challenges and thoughts

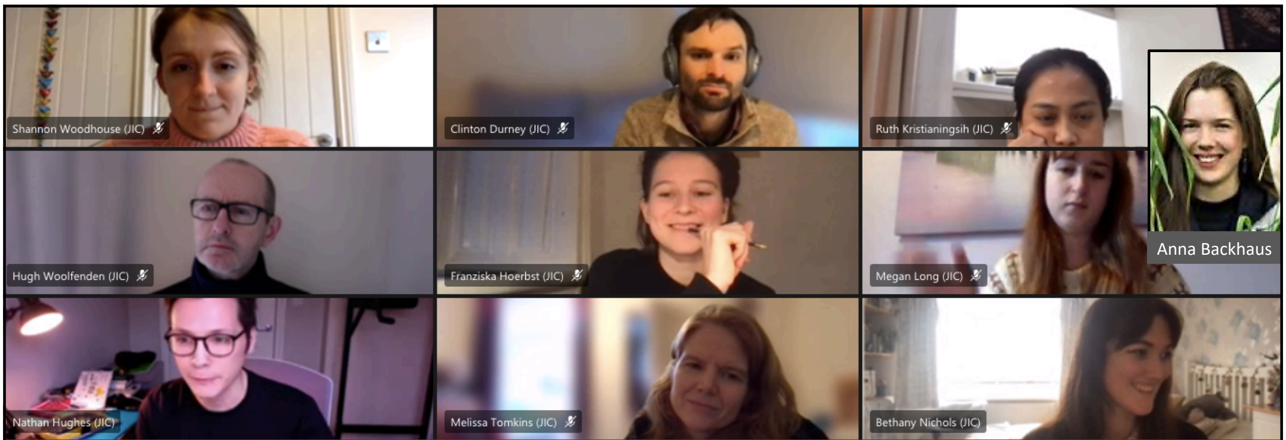
- Annotated balanced data sets
- Easy ways of sharing trained networks and retraining them (transfer learning)
- Better ways of accounting for uncertainties in the data
- Wishlist for linking to mechanistic models:
  - The ability to enforce thermodynamically consistent models
  - Better ways of extracting information from trained networks

40

Sometimes our understanding of the physics is outperformed by Deep Learning approaches



41



erc
European Research Council
Established by the European Commission

Thank you!

The Alan Turing Institute

UKRI Biotechnology and Biological Sciences Research Council

42