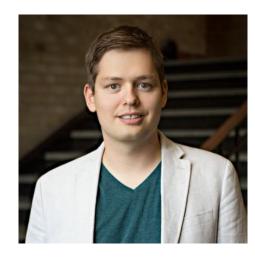
Artificial Intelligence in Plant Phenomics



Ian Stavness

Associate Professor Computer Science University of Saskatchewan Ian.Stavness@usask.ca

Artificial Intelligence Applications to Agriculture Texas A&M 16 July 2020







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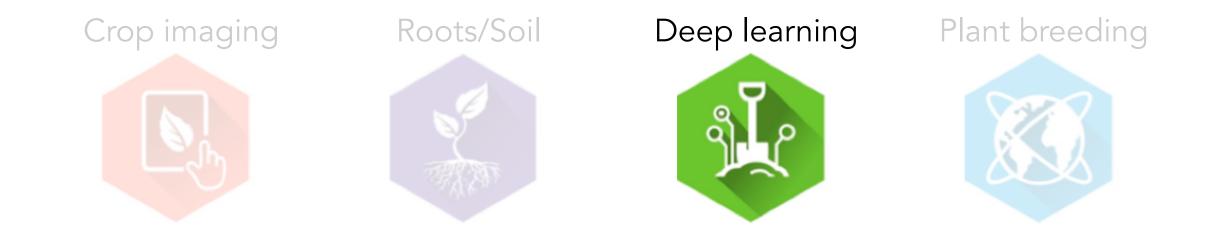


Crop Development Center, Saskatoon, Canada

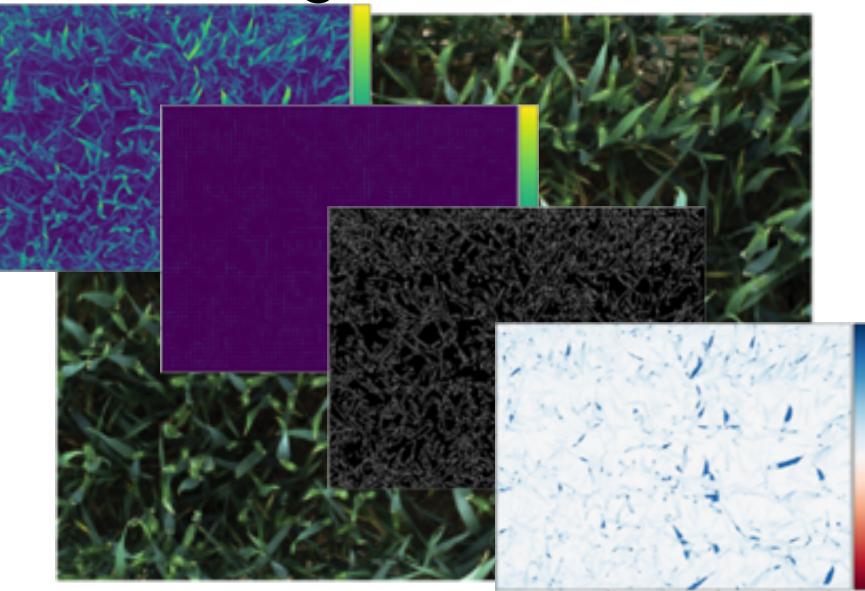






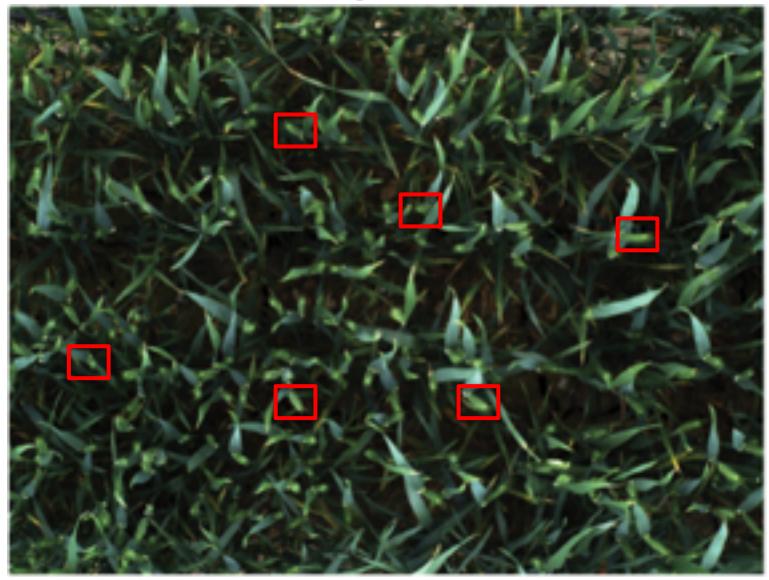


Selecting features is hard



Sadeghi-Tehran et al. (2017). Automated Method to Determine Two Critical Growth Stages of Wheat: Heading and Flowering. *Front. in Plant Sci., 8*(February), 1–14.

Deep learning is representation learning

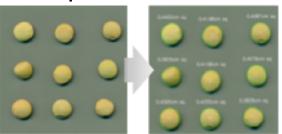


Sadeghi-Tehran et al. (2017). Automated Method to Determine Two Critical Growth Stages of Wheat: Heading and Flowering. *Front. in Plant Sci.*, 8(February), 1–14.

Imaging & Deep Learning for Agriculture

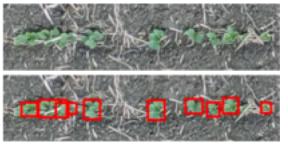
Seed scale

seed phenotyping, provenance



Plant scale

identifying plants, estimating traits



early disease detection

crop damage, crop insurance

Field scale

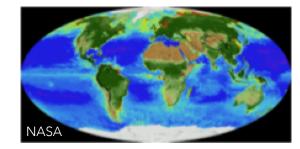
crop health,

precision management

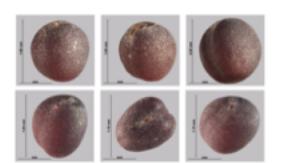
Global scale

yield prediction, price forecasting





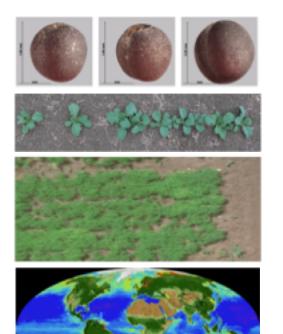
weather prediction, logistics



automated seed inspection

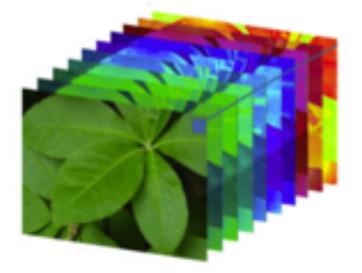
Learned Features across Scales

Spatial

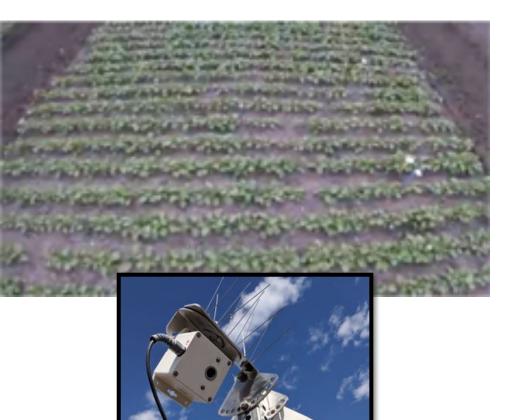


Spectral

Temporal

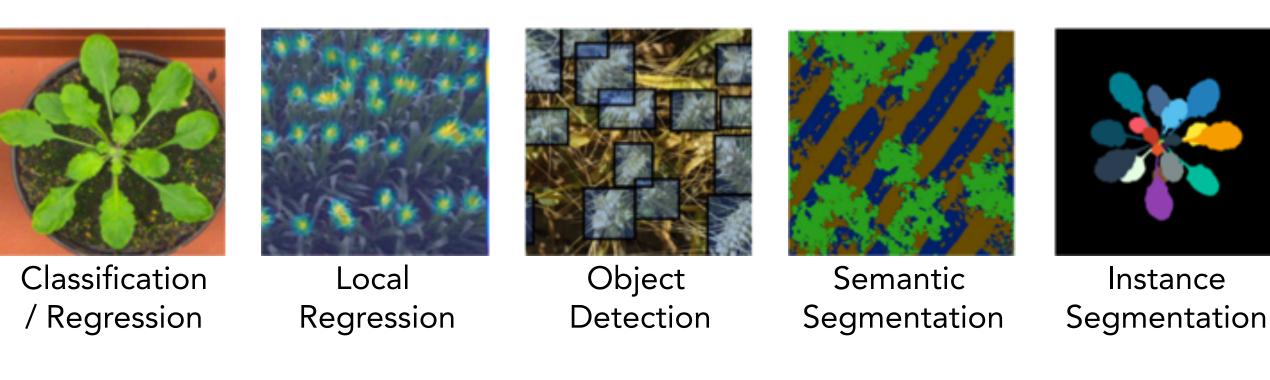


(Mishra et al. 2017)



"Camera On A Stick"

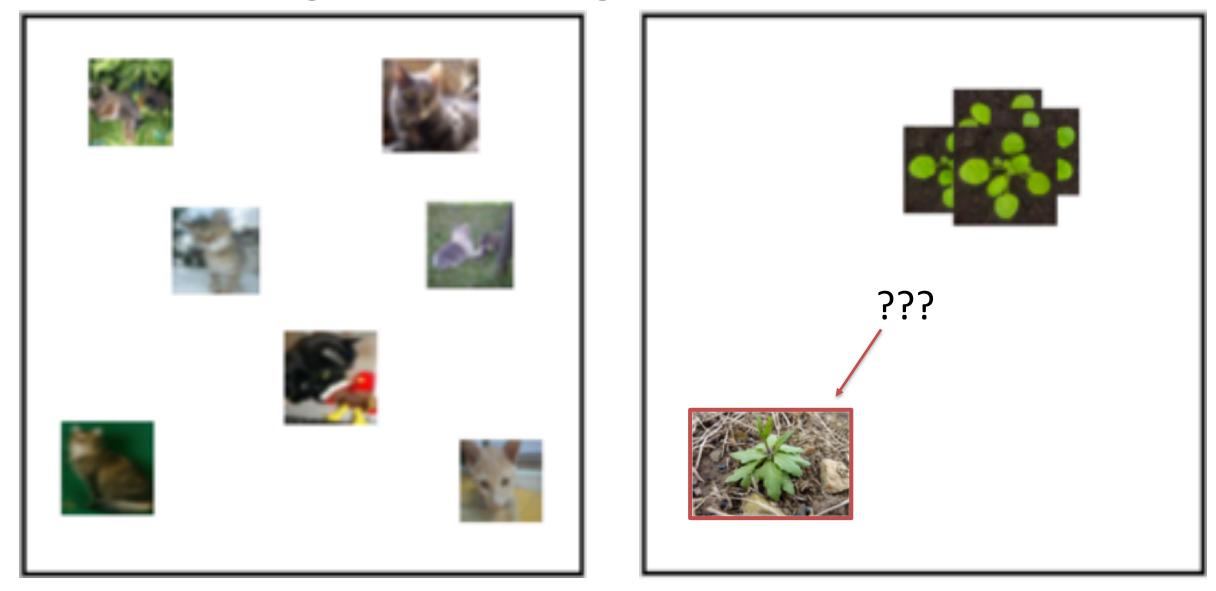
Image-based Phenotyping



Deep Plant Phenomics

https://github.com/p2irc/DeepPlantPhenomics

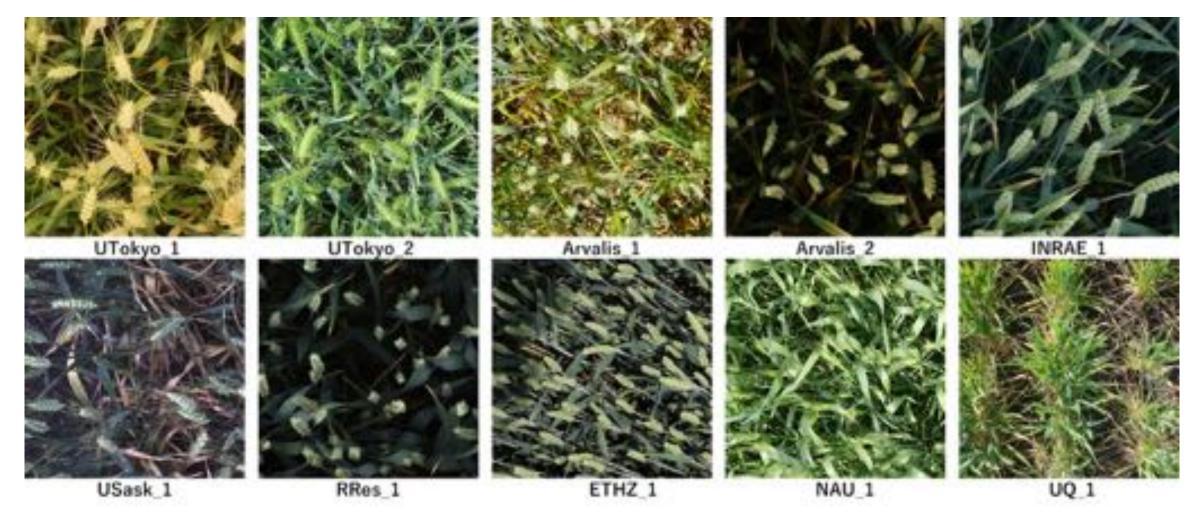
Challenge #1: Large diverse datasets



New open datasets Global Wheat Head Dataset

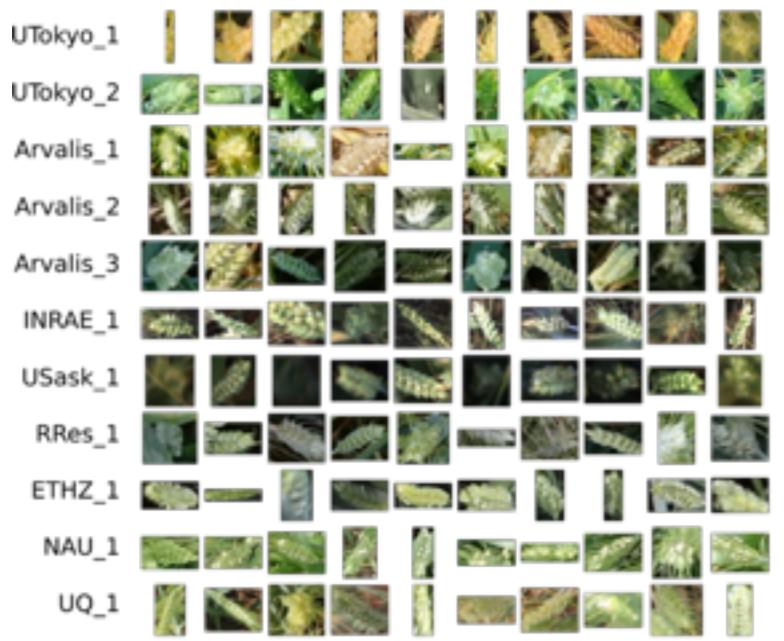


Global Wheat Head Detection Dataset



David, E., Madec, S., Sadeghi-Tehran, P., Aasen, H., Zheng, B., Liu, S., Pozniak, C., Stavness, I., Guo, W. (2020). Global Wheat Head Detection (GWHD) dataset. Plant Phenomics, *in press*.

Global Wheat Head Detection Dataset





Competition for CVPPP 2020

Research Code Competition

Global Wheat Detection

Can you help identify wheat heads using image analysis?

University of Saskatchewan · 1,799 teams · 19 days to go (12 days to go until merger deadline)

Overview Data Notebooks Discussion Leaderboard Rules Host

\$15,000

Prize Money

Join Competition

Edit

Overview

Description

Evaluation

Timeline

Open up your pantry and you're likely to find several wheat products. Indeed, your morning toast or cereal may rely upon this common grain. Its popularity as a food and crop makes wheat widely studied. To get large and accurate data about wheat fields worldwide, plant



Global Wheat Data: Future Contributions



https://global-wheat.com

PlotVision

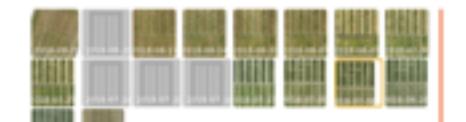


Nasser Kernen 2018 IXU1000 Trial Map 0 GCPs Uploaded





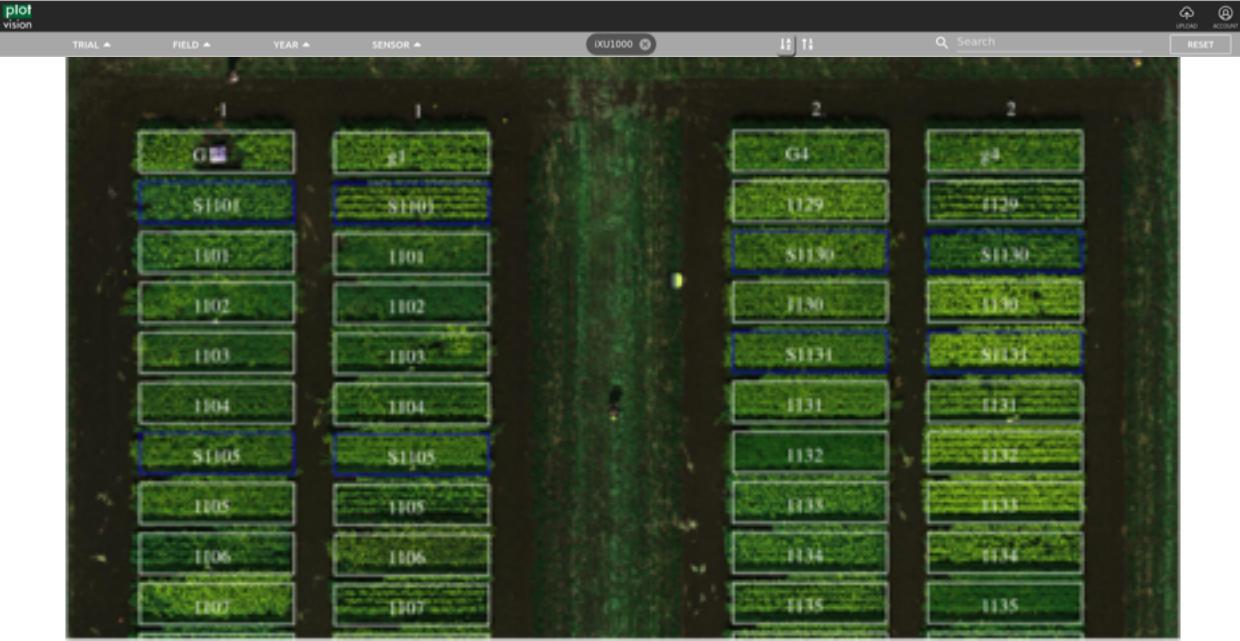






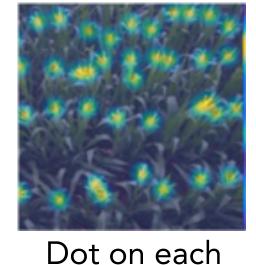
front at loss.

PlotVision



Challenge #2: Image annotation

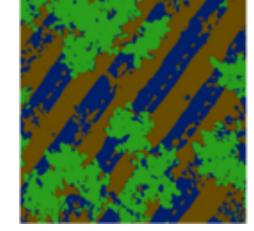




object



Box around each object



Draw outlines



Draw outlines for each object



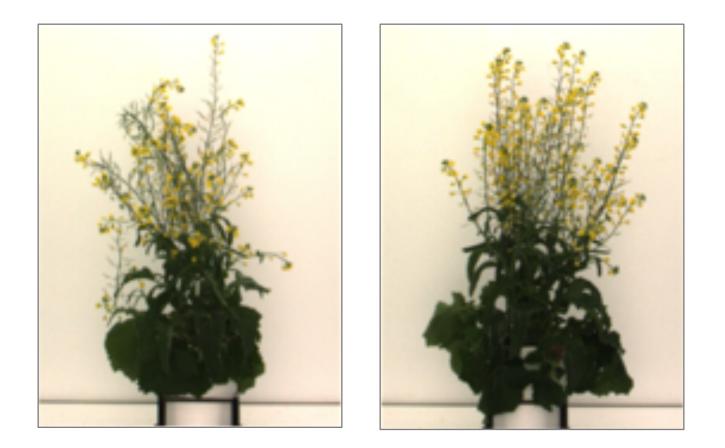
whole image



Latent Space Phenotyping

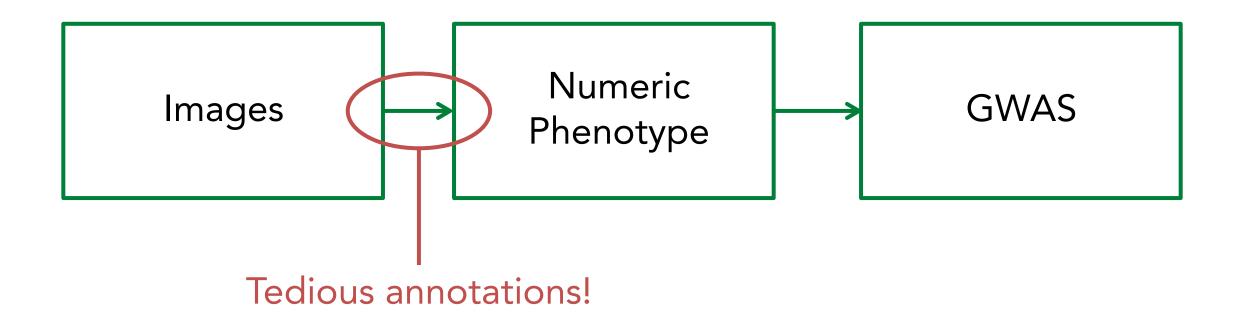
Phenotype-to-genotyping mapping for stress resistance

https://github.com/p2irc/LSPlab



Ubbens, J., Cieslak, M., Prusinkiewicz, P., Parkin, I., Ebersbach, J., & Stavness, I. (2020). Latent space phenotyping: automatic image-based phenotyping for treatment studies. Plant Phenomics, 2020, 5801869

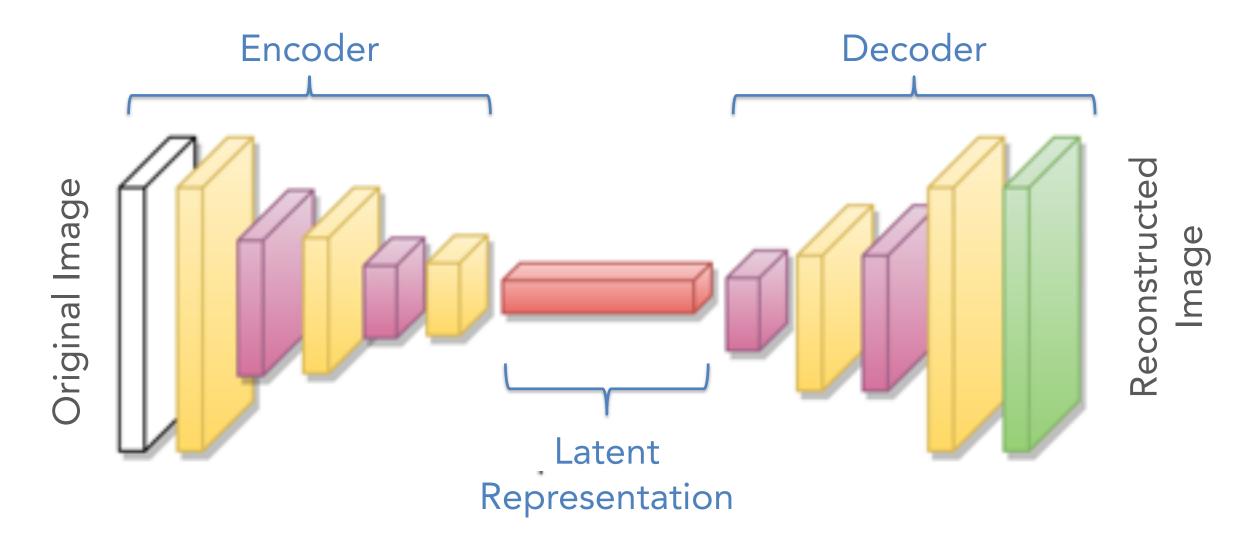
Image-based Phenotyping



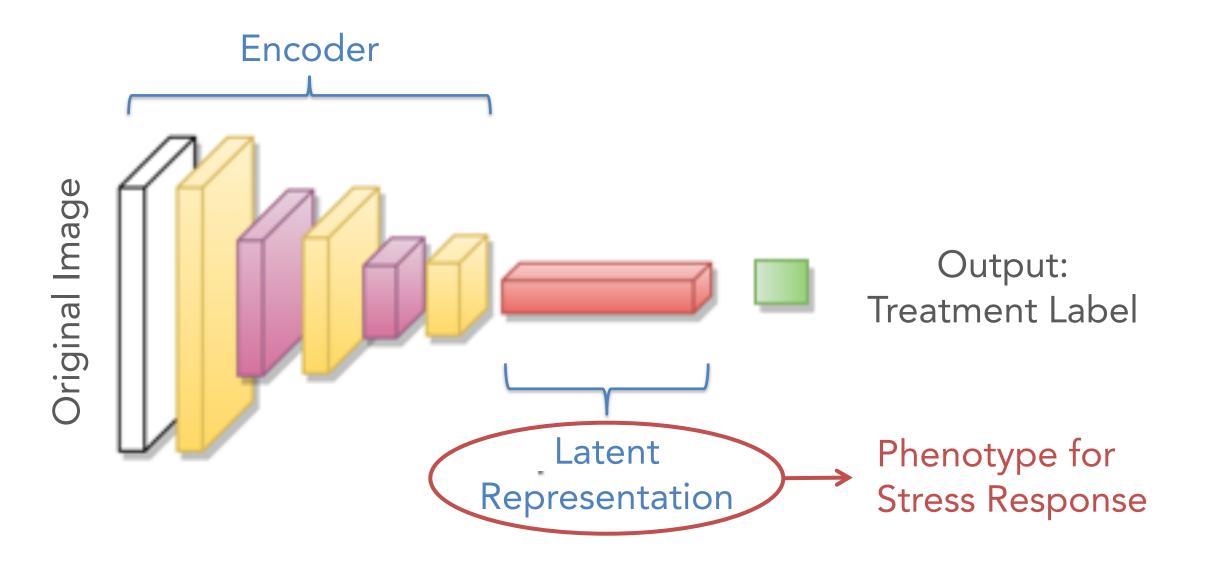
Latent Space Phenotyping



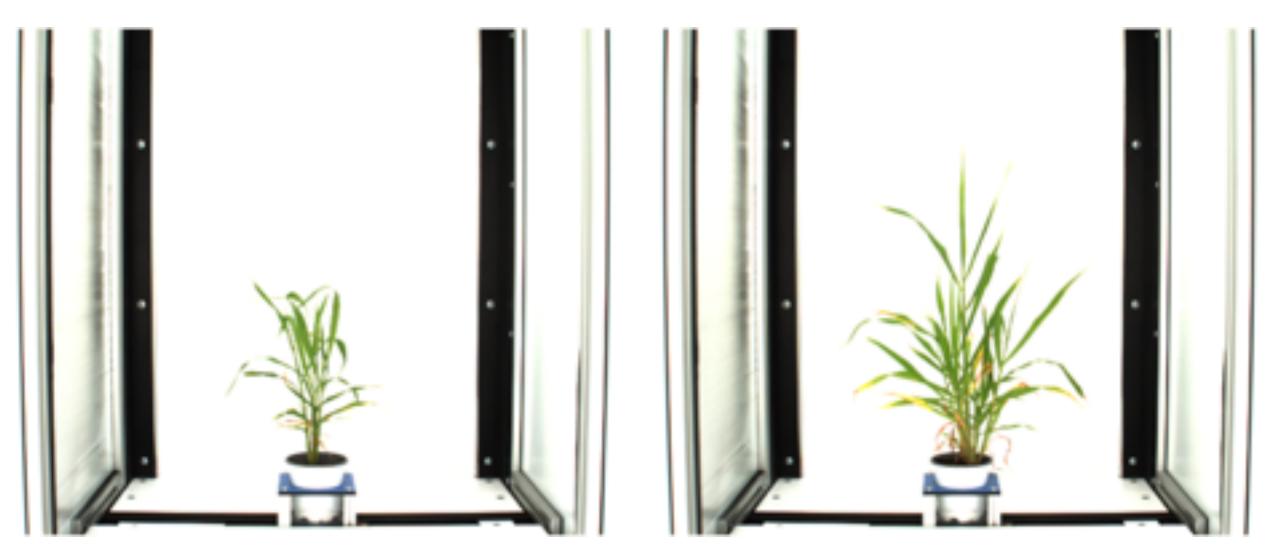
Latent variable models



Latent variable models

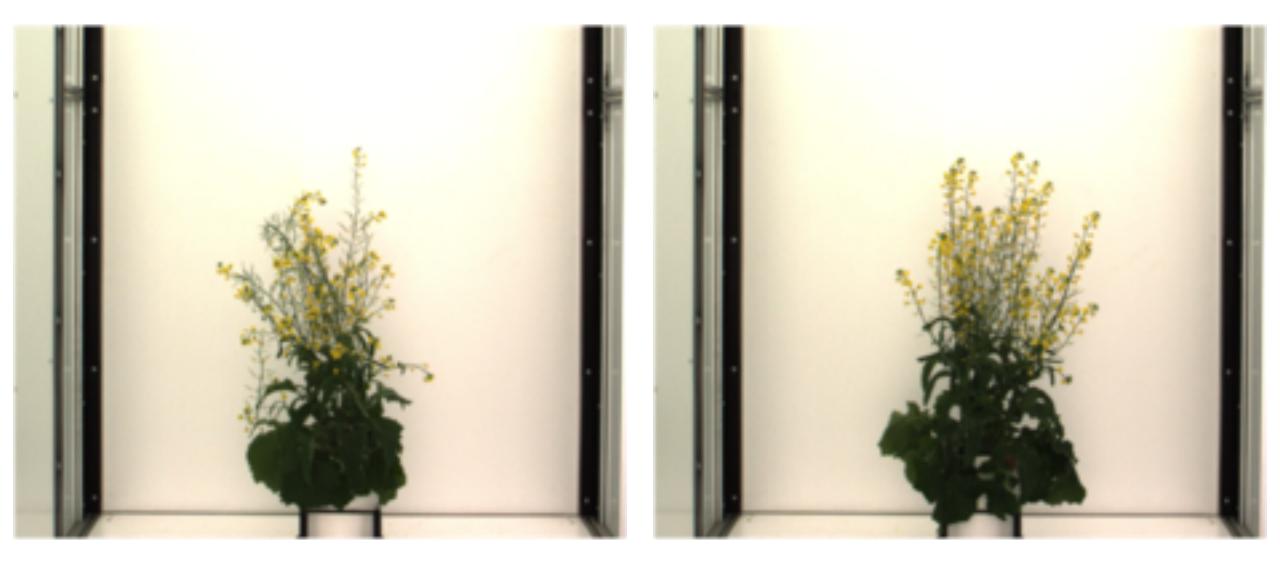


Datasets: Setaria RIL

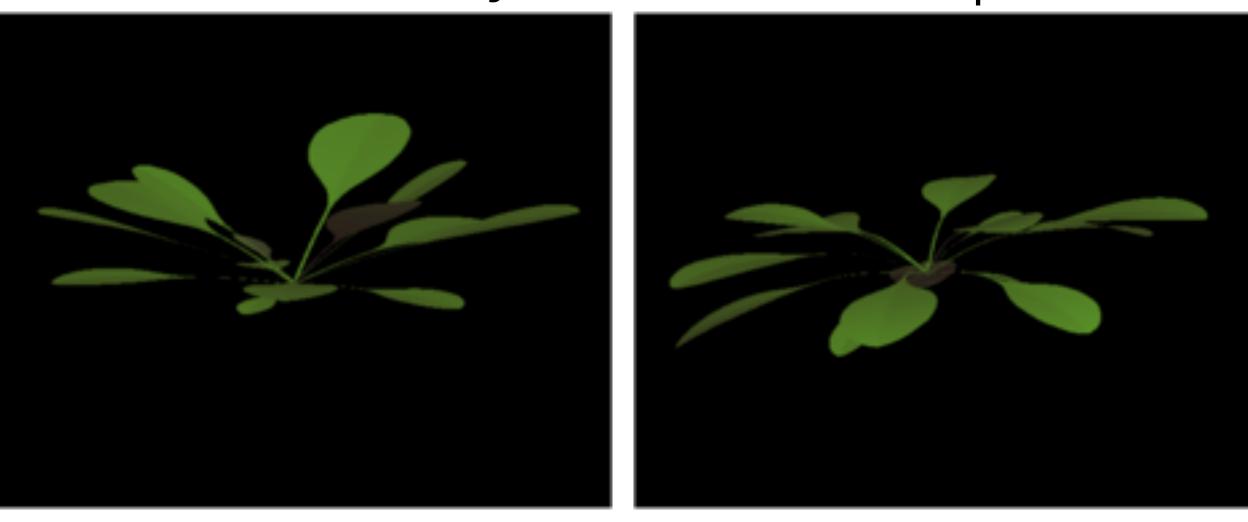


Feldman et al. (2018). Components of Water Use Efficiency Have Unique Genetic Signatures in the Model C ₄ Grass Setaria. Plant Phys., 178(2), 699–715.

Datasets: Canola NAM

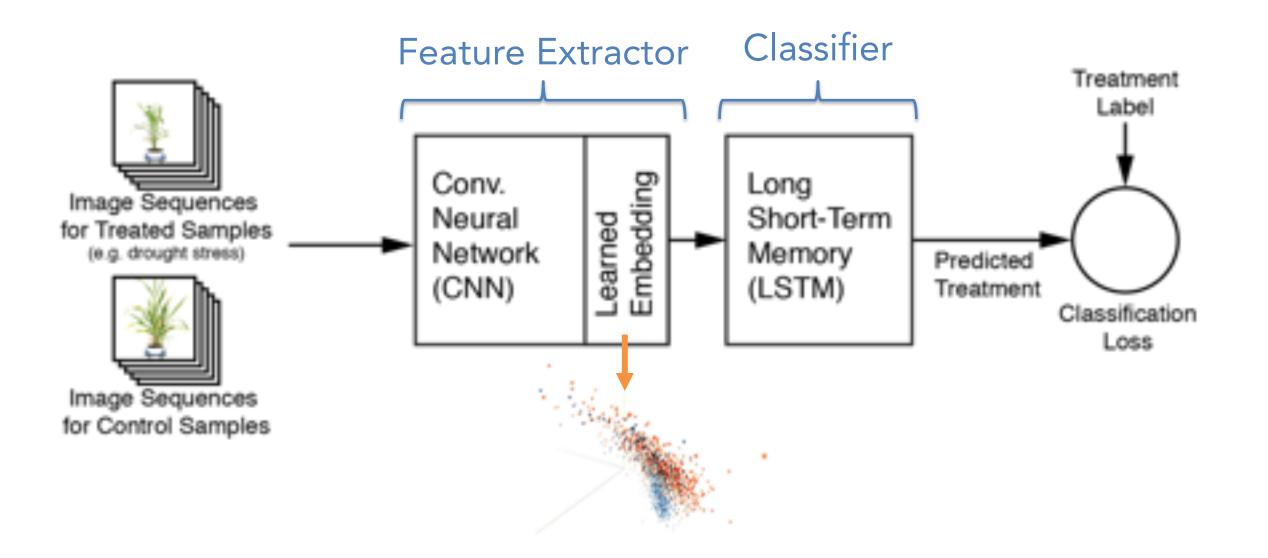


Datasets: Synthetic Arabidopsis

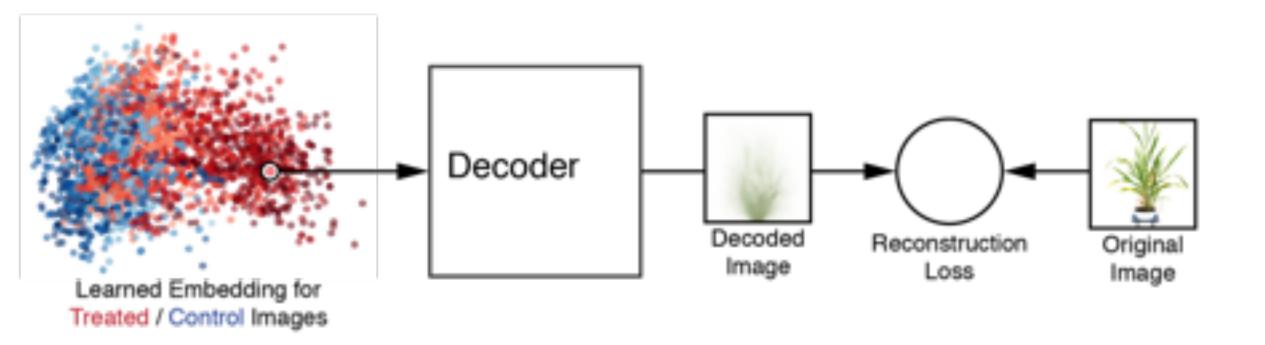


- Genomic data from the A. thaliana polymorphism database
- Images generated from a 3D L-system model

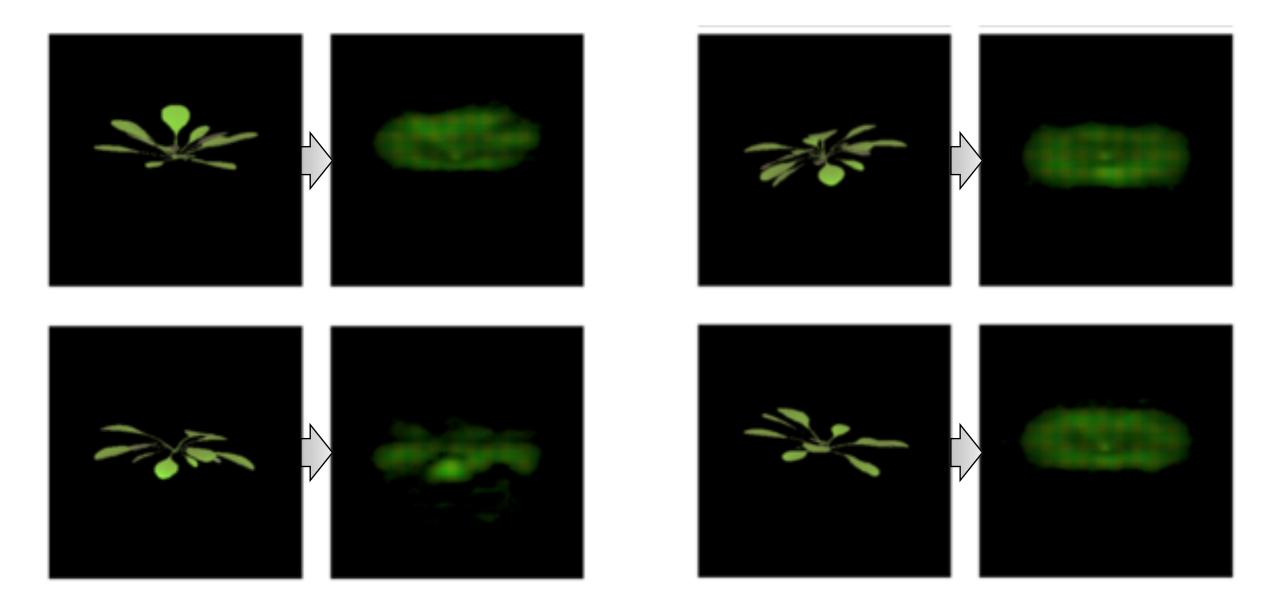
Embedding Process



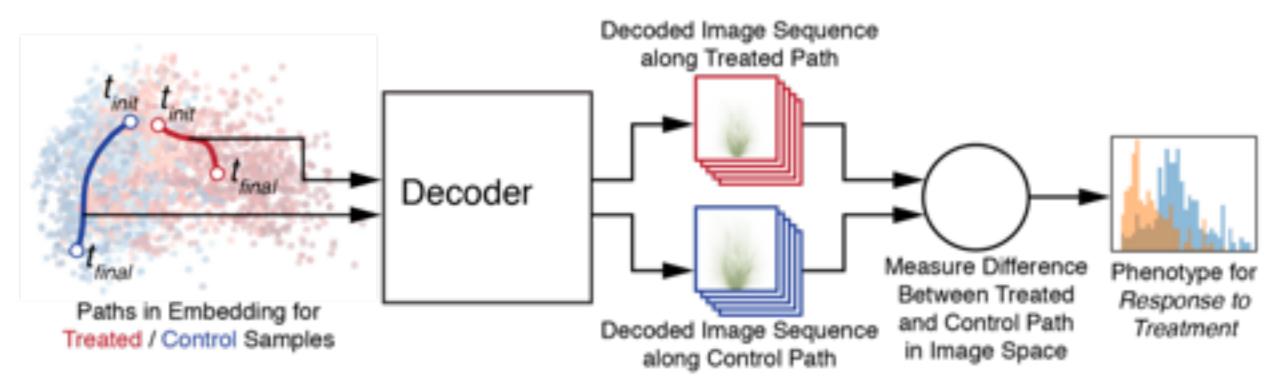
Decoding Process



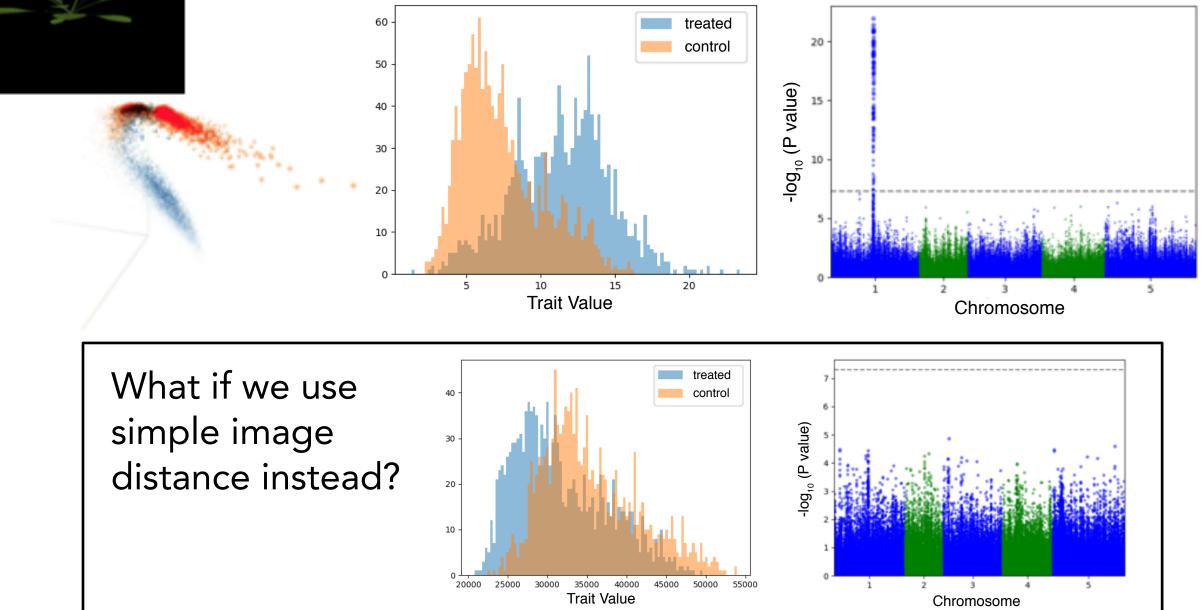
Example decoded images

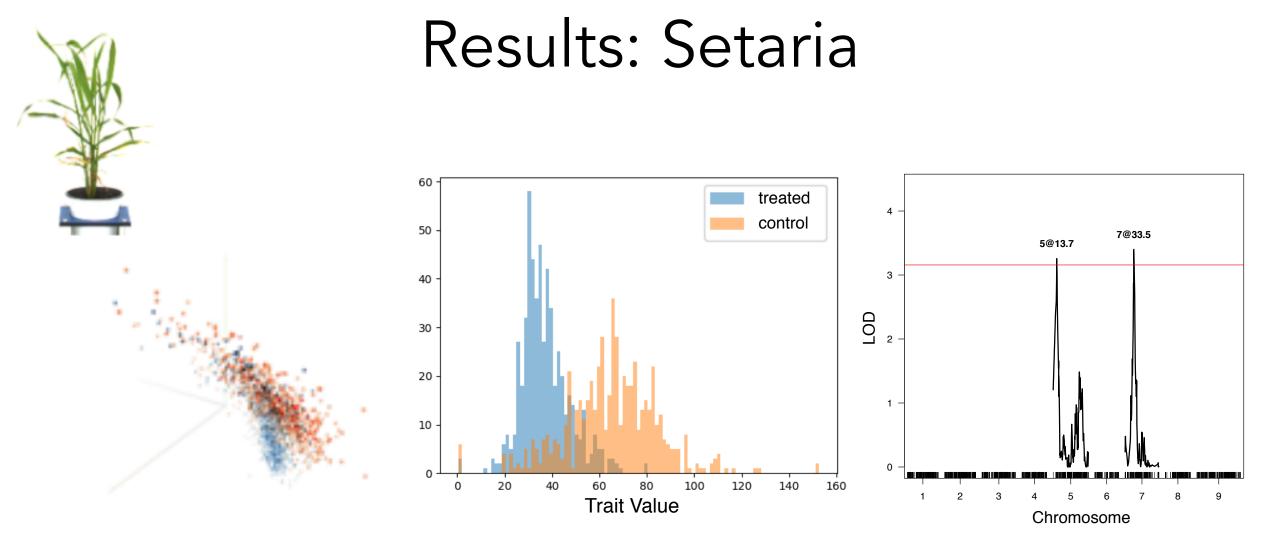


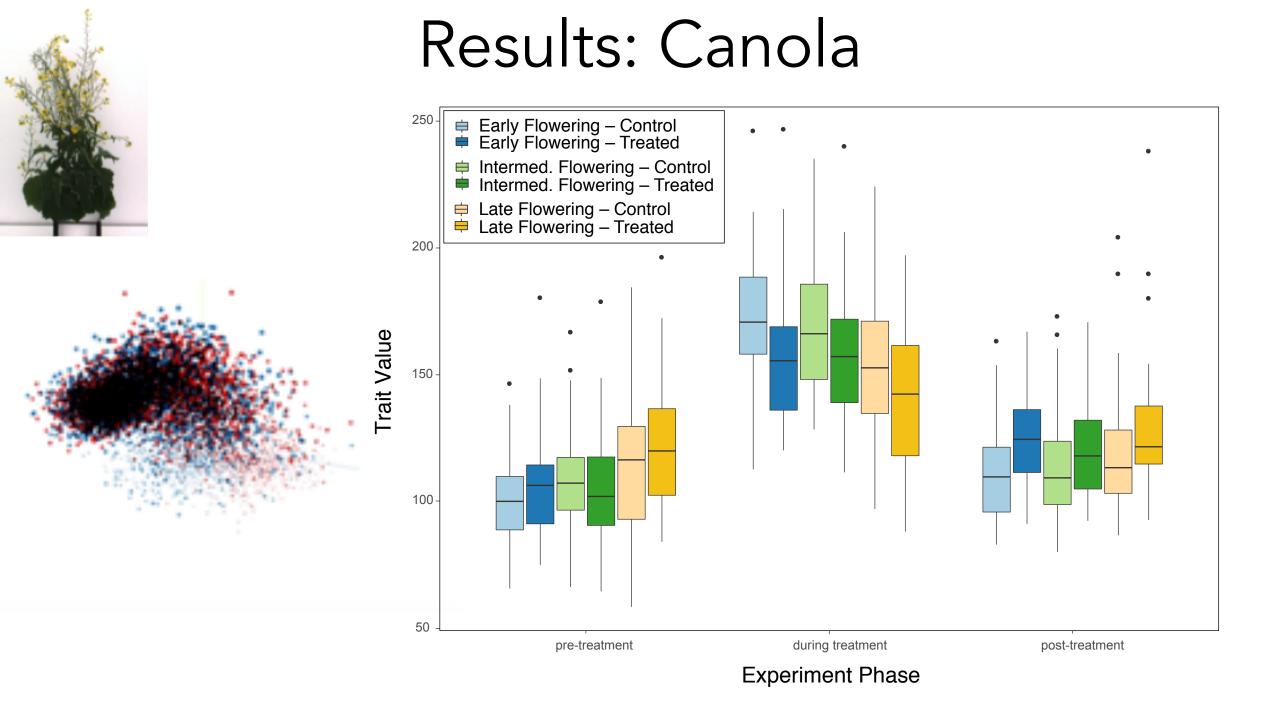
Measuring Response-to-Treatment



Results: Synthetic Arabidopsis





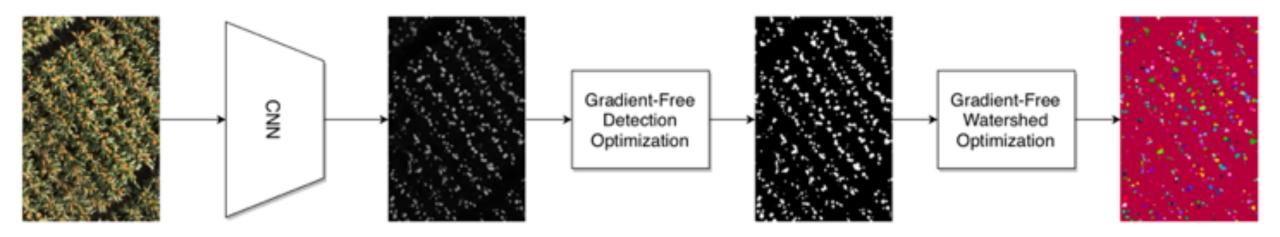


Limitation: Explainability



AutoCount: Unsupervised Organ Counting

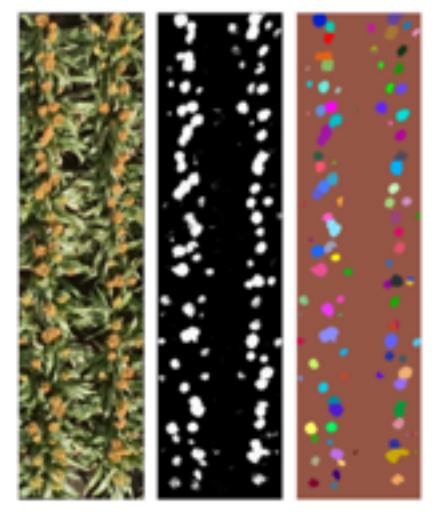
To appear: www.plant-phenotyping.org/CVPPP2020



Ubbens, J., Ayalew, T., Shirtliffe, S., Josuttes, A., Pozniak, C. & Stavness, I. (2020). AutoCount: Unsupervised Segmentation and Counting of Organs in Field Images. ECCV Workshops, 2020, to appear.

AutoCount: Unsupervised Organ Counting

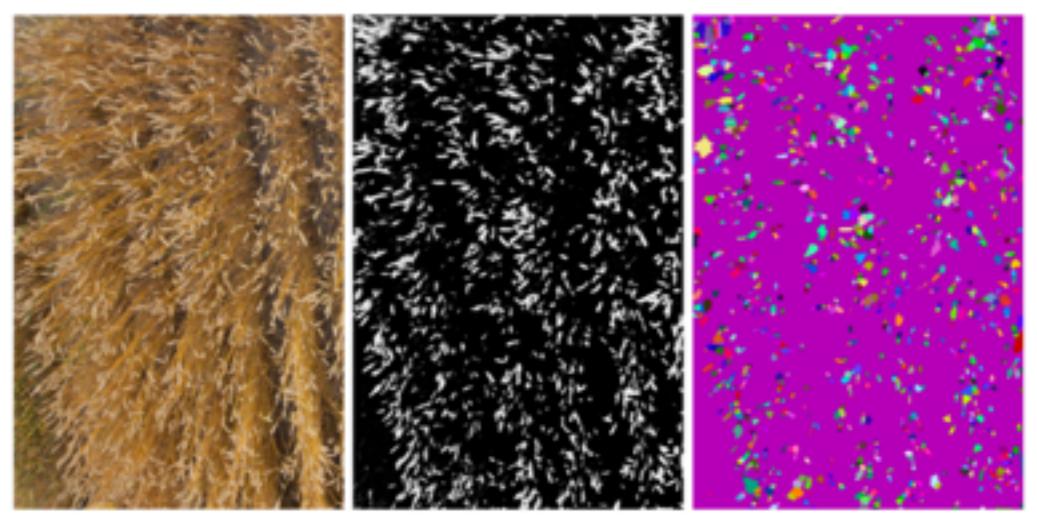
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Ubbens, J., Ayalew, T., Shirtliffe, S., Josuttes, A., Pozniak, C. & Stavness, I. (2020). AutoCount: Unsupervised Segmentation and Counting of Organs in Field Images. ECCV Workshops, 2020, to appear.

AutoCount: Unsupervised Organ Counting

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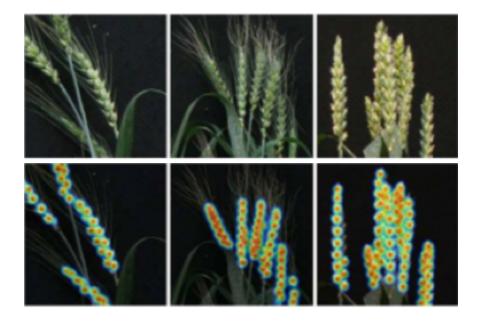


Ubbens, J., Ayalew, T., Shirtliffe, S., Josuttes, A., Pozniak, C. & Stavness, I. (2020). AutoCount: Unsupervised Segmentation and Counting of Organs in Field Images. ECCV Workshops, 2020, to appear.

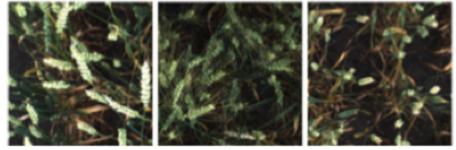
Domain Adaptation for Organ Counting

To appear: www.plant-phenotyping.org/CVPPP2020

Source: Indoor labeled dataset



Target: Outdoor *Unlabeled* dataset



GWHD

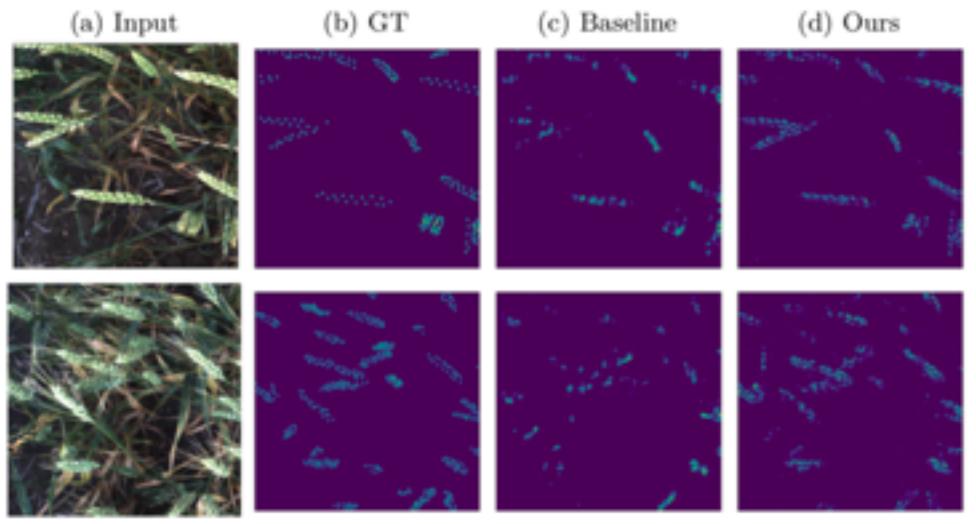


CropQuant

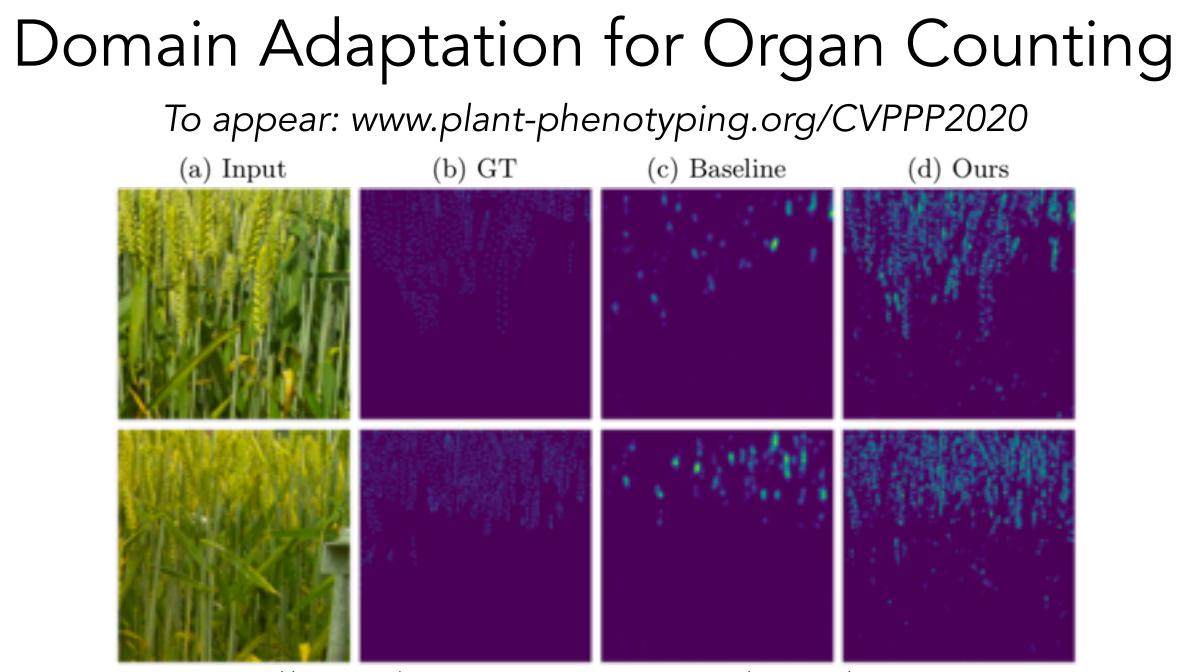
Ubbens, J., Ayalew, T., & Stavness, I. (2020). Unsupervised Domain Adaptation For Plant Organ Counting. ECCV Workshops, 2020, *to appear*.

Domain Adaptation for Organ Counting

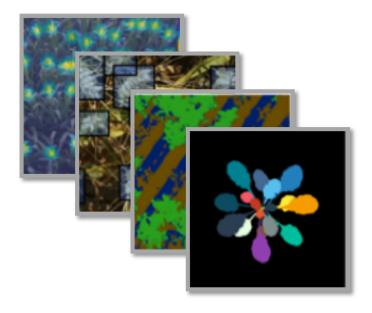
To appear: www.plant-phenotyping.org/CVPPP2020



Ubbens, J., Ayalew, T., & Stavness, I. (2020). Unsupervised Domain Adaptation For Plant Organ Counting. ECCV Workshops, 2020, *to appear*.



Ubbens, J., Ayalew, T., & Stavness, I. (2020). Unsupervised Domain Adaptation For Plant Organ Counting. ECCV Workshops, 2020, *to appear*.





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