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Catch the carbon
CLIMATE SOLUTIONS IN THE LAND USE SECTOR

Generative adversarial networks for agricultural image generation and generative super resolution

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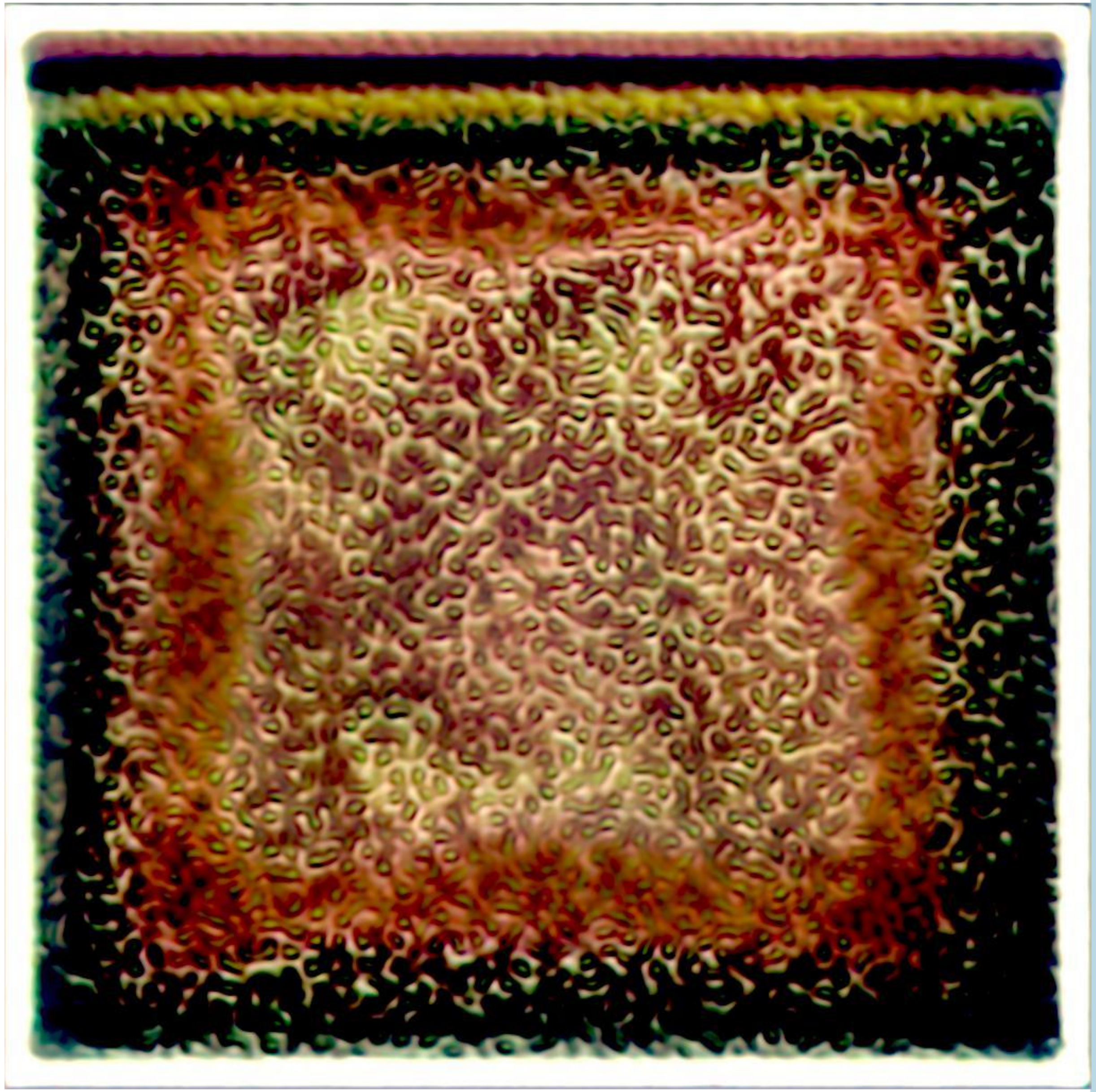
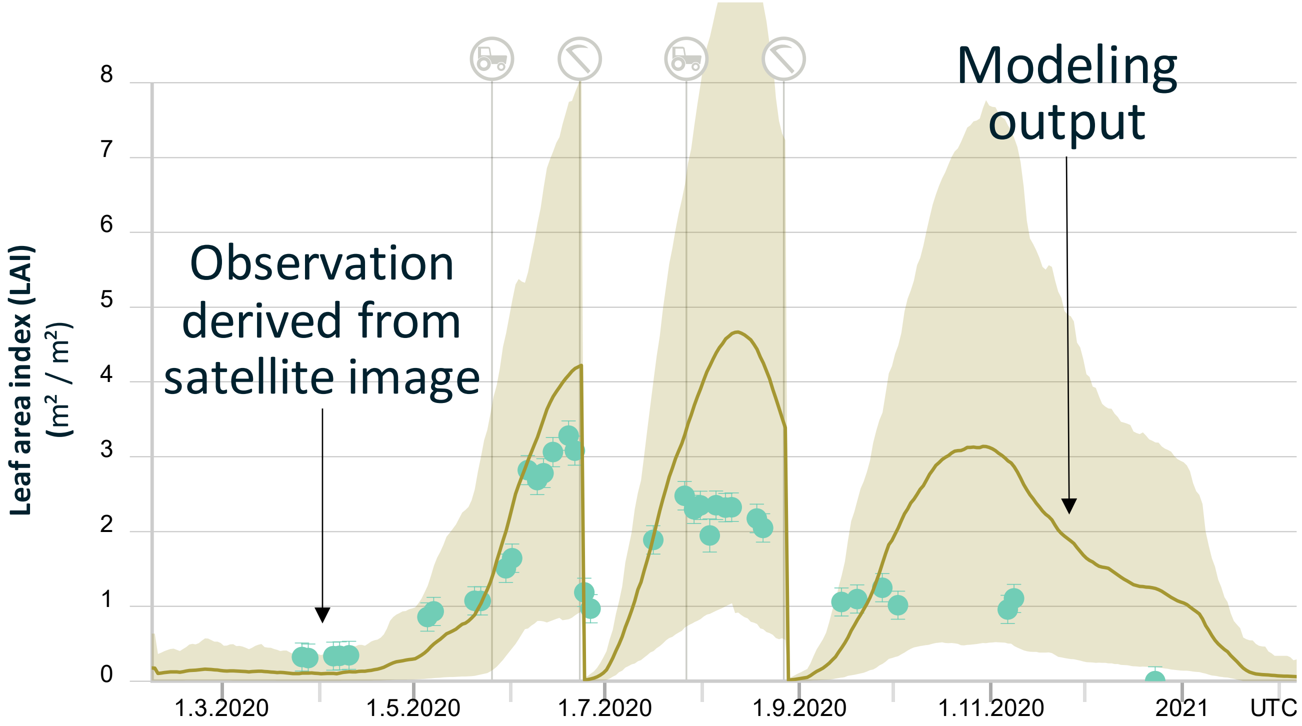


Vegetation remote sensing

- Needed for example in crop modeling in carbon sequestration research, see fieldobservatory.org
- Especially important when scaling up to thousands of farms



Satellite image-derived LAI and STICS model hindcast from Qvidja farm with 90 % confidence intervals. Source: https://www.fieldobservatory.org/en/online-field-data/?site=qvidja

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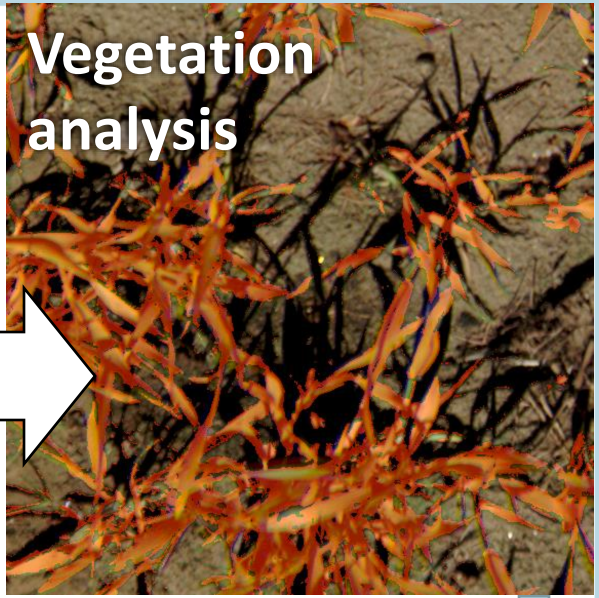
Image: ESA



What if we could
go from here… …to/or here … …then here, analyze,

and infer our results back?

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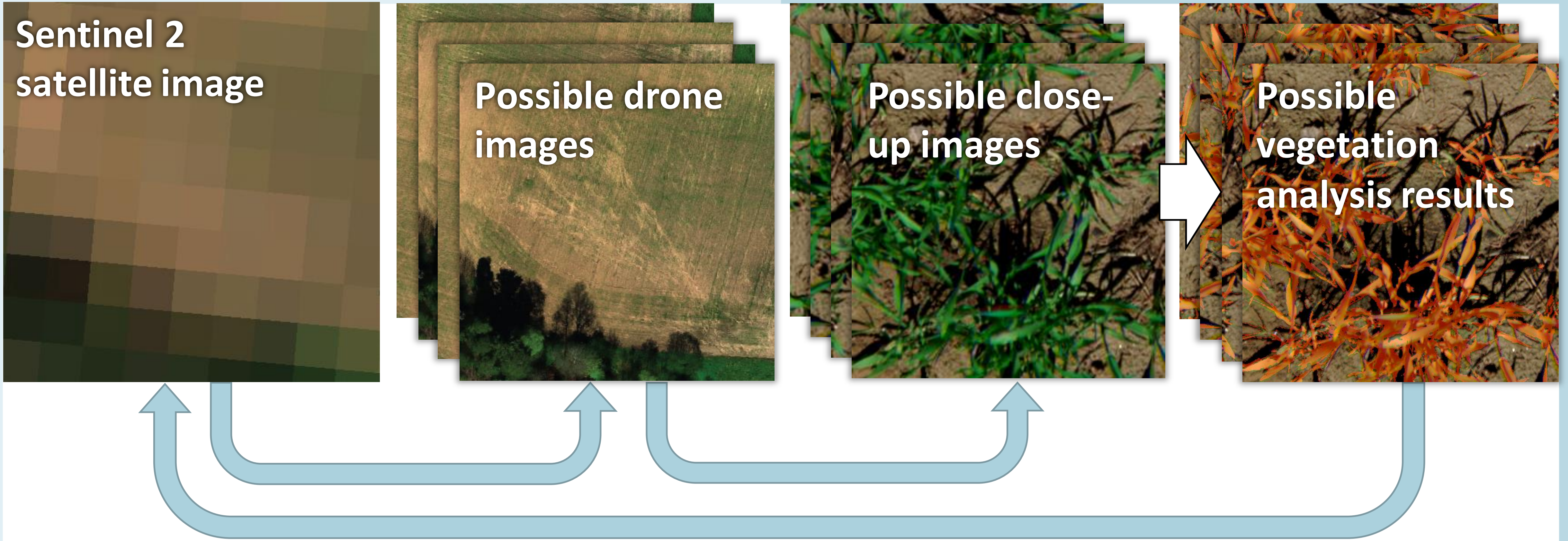

Need to work with distributions and statistics, and plenty of uncertainty.

Generative model

- Generates data points that follow an approximate distribution of real data

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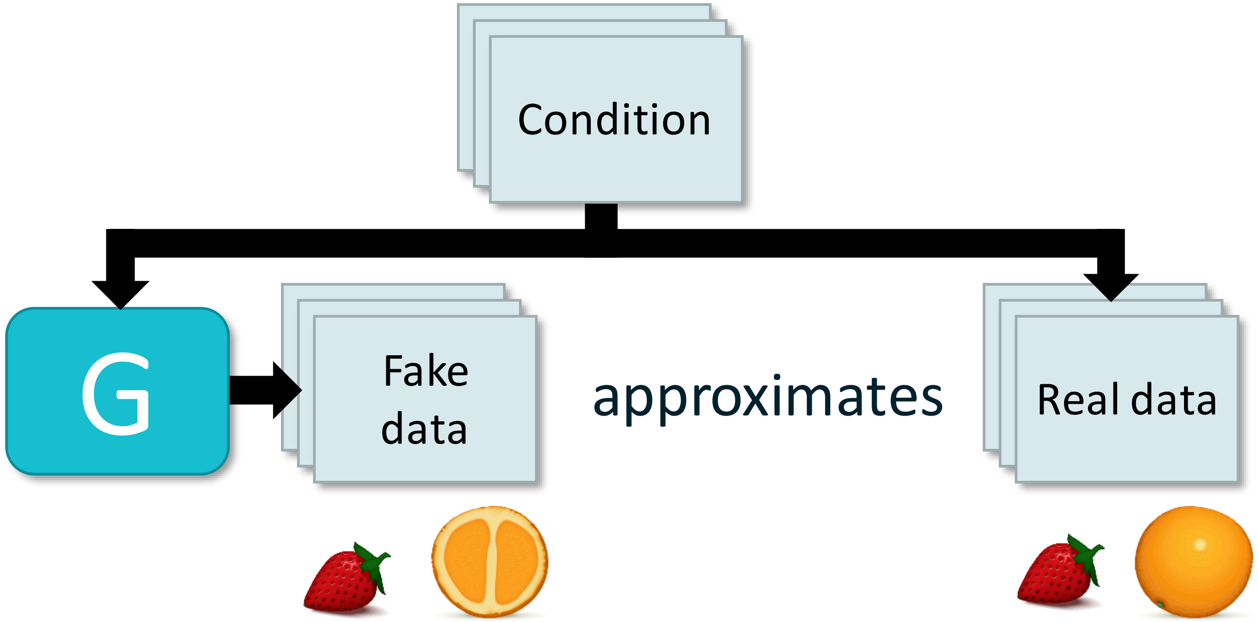
Conditional generative model

- A conditional generative model randomly generates data points that follow an approximate conditional distribution of real data



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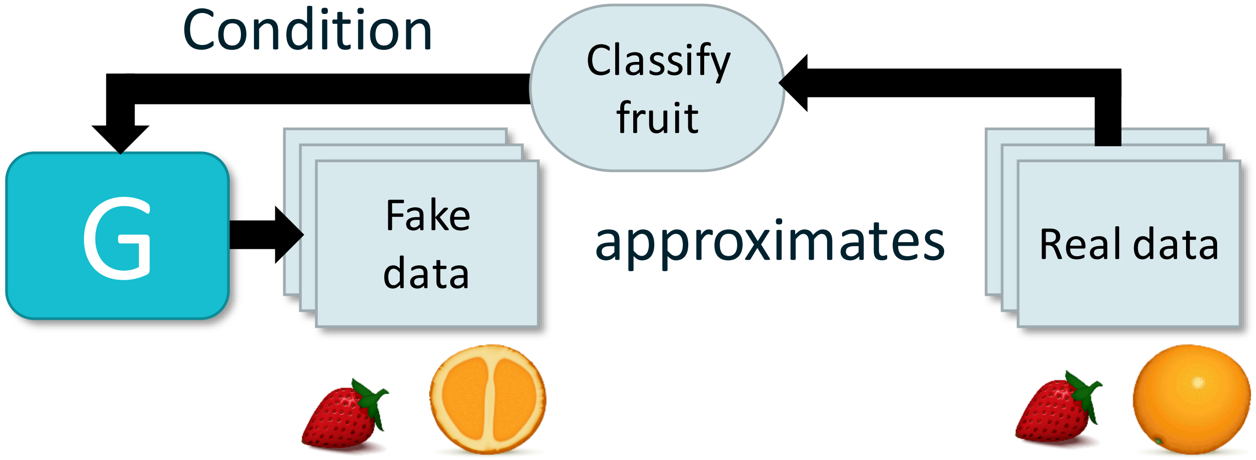
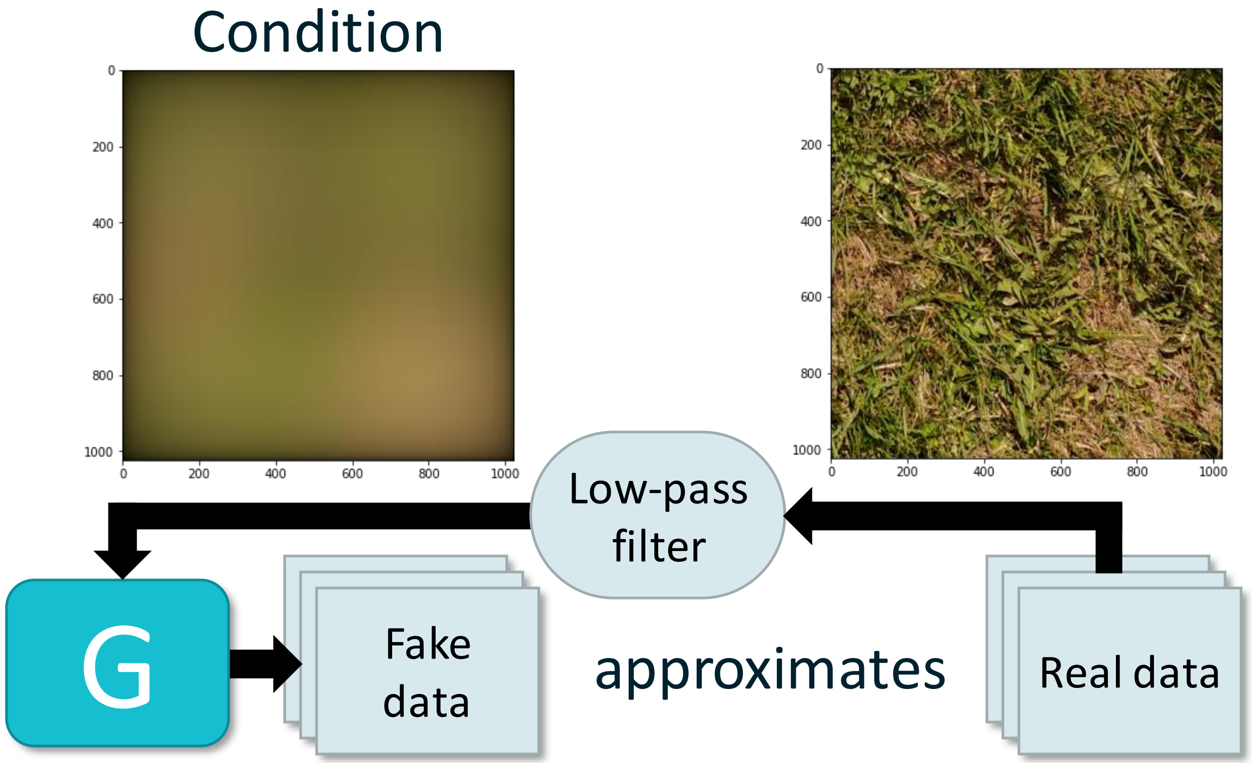
Conditional generative model

- The condition can be a function of the data



Generative super resolution

- Fake data is conditioned on low-pass filtered (blurred) real data



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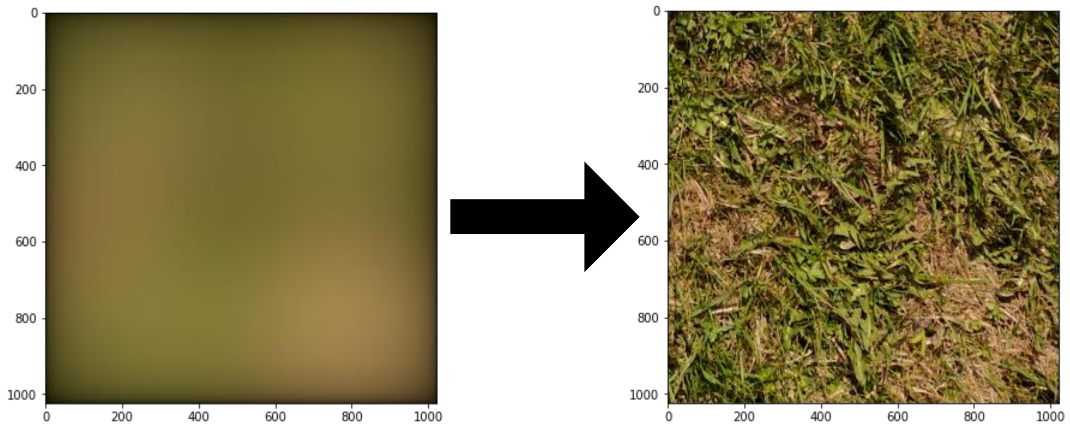
Toy problem statement

- Acquire training images of lawns with various degrees of vegetation cover
- Train a generative model on the data
  - Given a low-resolution image of the lawn as conditioning input, the model shall sample from the approximate distribution of what the lawn might look like at high resolution
  - The model shall be able to handle arbitrarily large images

Ideally…



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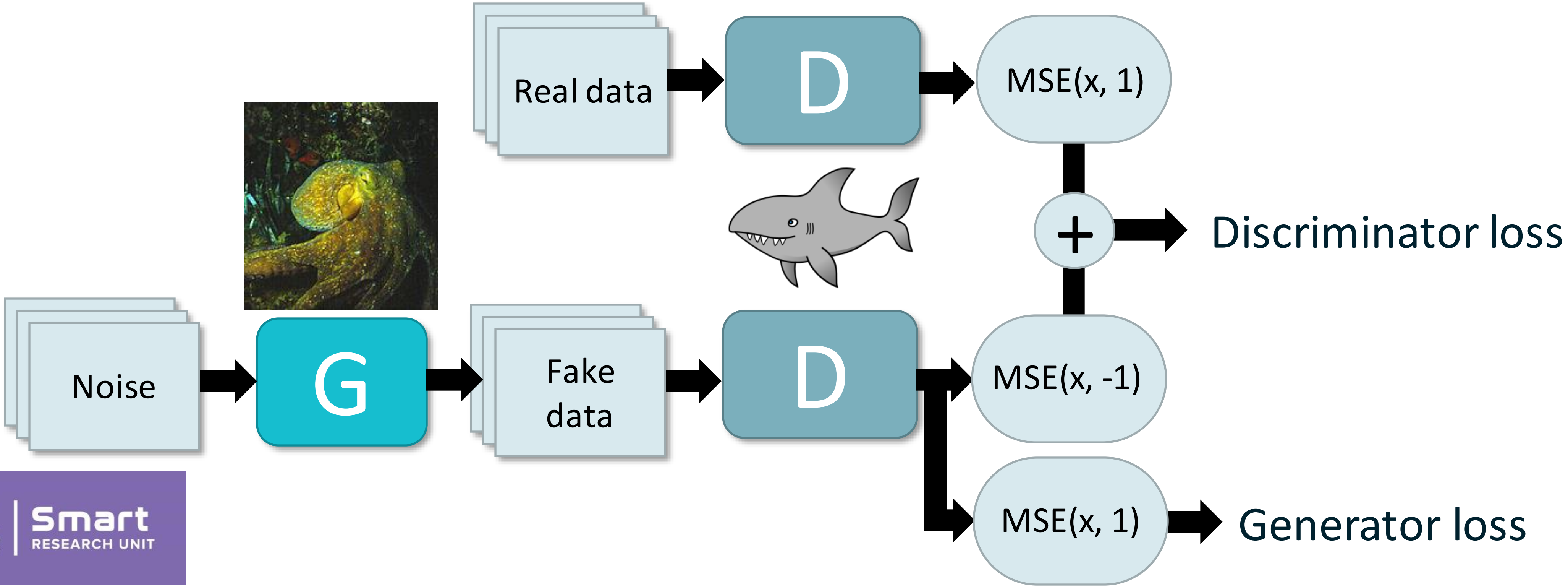
Toy training dataset

Least square generative adversarial network

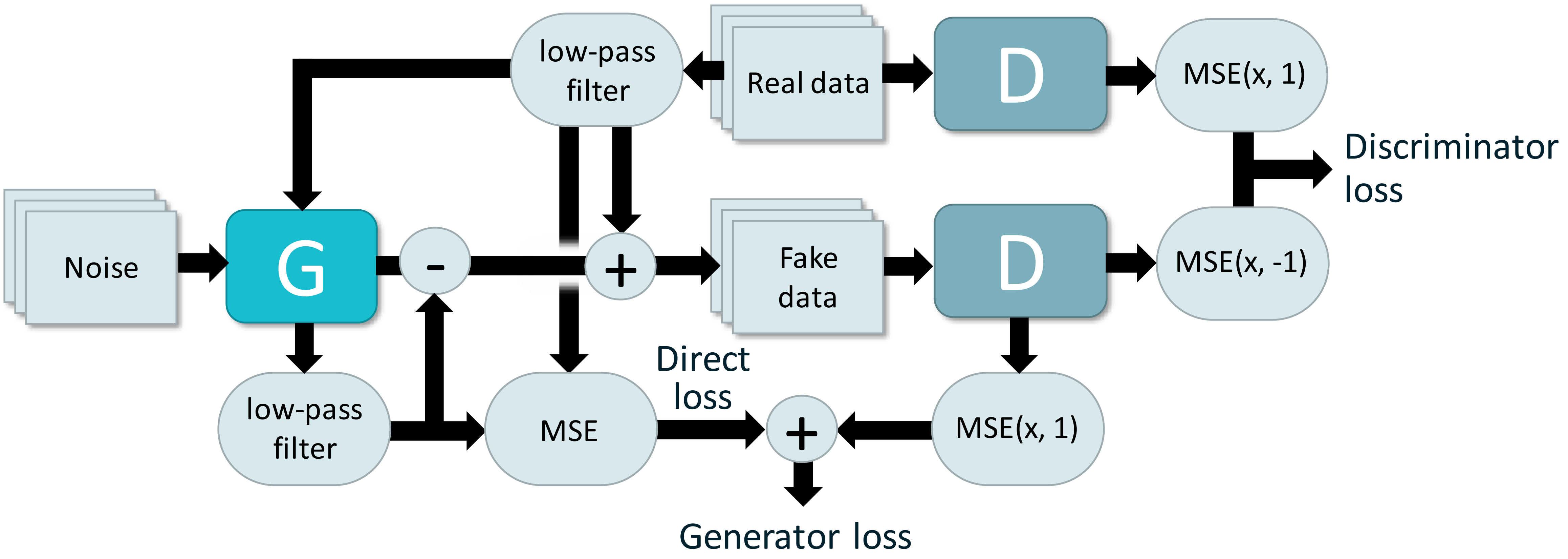
- A machine learning method, a variant of GAN

arXiv:1406.2661 [stat.ML], arXiv:1611.04076 [cs.CV]

- Generator (G) and discriminator (D) networks compete to minimize their respective losses



Our super-resolution GAN training setup



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- Also: additive noise, rotation and exposure augmentation of discriminator input, gradient accumulation, stochastic gradient descent with random training image selection and random cropping

Our model design

- Generator and discriminator are convolutional neural networks – locality!
  - Batch normalization, no pooling layers
  - Spatial data kept 2x oversampled throughout the network using isotropic anti-aliasing layers – translation invariance!

Generator

- Encoder-decoder with skip connections (8 level U-net)
- Noise input: 1024x1024x1, conditioning input: 1024x1024x3
- Output: 1024x1024x3
- Can generate arbitrarily large images piecemeal from deterministic noise input

Discriminator

- Encoder structure (first half of 7 level U-net)
- Input: 1024x1024x3 center-cropped to 512x512x3
- Output: 8x8x1
- Output center-cropped to 2x2x1 for adversarial loss

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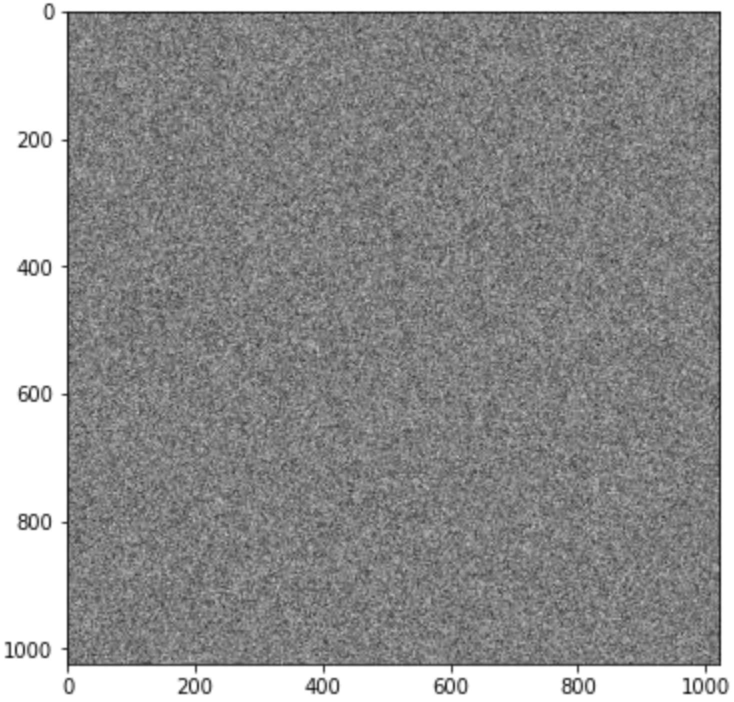
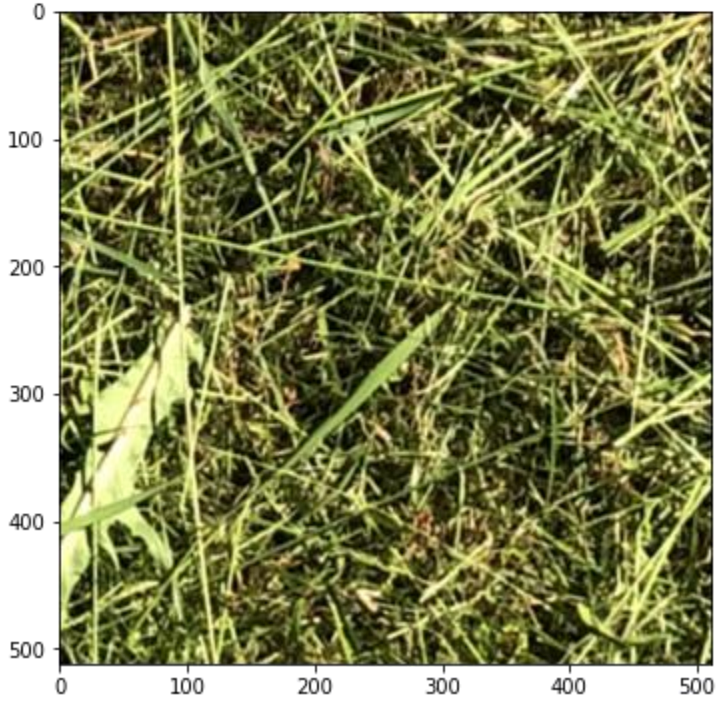
Early training video on another toy dataset: https://youtu.be/Ecz4kHMEE7o

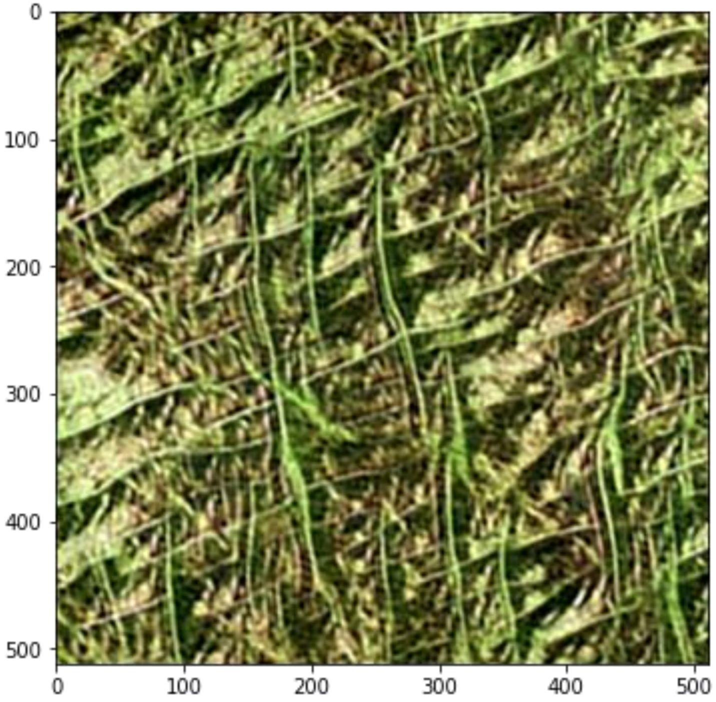
Toy problem preliminary results



Noise input

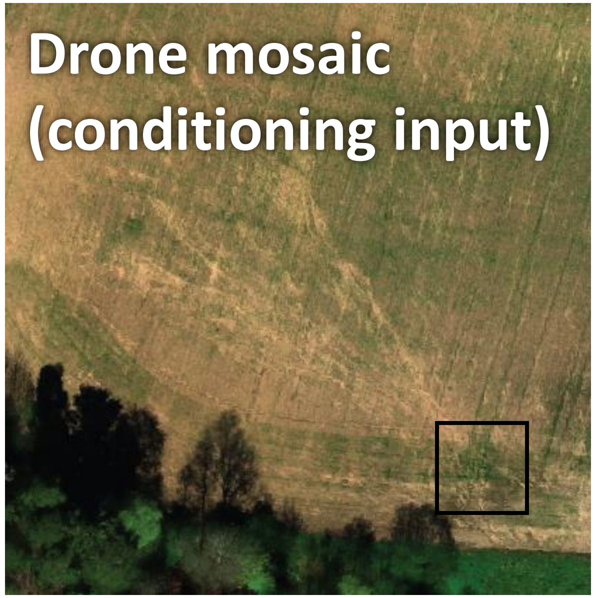


Real data



Fake data

Toy problem preliminary results



Generated image

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✔ ”Vegetation” ✔ Nearly seamless 256x256 tiling

✘ Realistic vegetation ✘ Realistic soil

Discussion and future work

- GAN improvements
  - Tune the model structure
  - Design more optimal anti-aliasing filters
  - Try calculating products of feature maps. Controlled bandwidth: c = a * b ➔ bandwidth(c) = bandwidth(a) + bandwidth(b)
  - Try other models than pure convolutional networks, say Vision Transformers
  - Steerable network?

Discussion and future work

- Current super-resolution model drawback: Vegetation is assumed to be independent in two locations separated by tens of cm. Add a flat noise input!
- A time series of training images would be more informative than a single image from each location
- Generate 3-d models of vegetation
- Train generative models for transforming images between different sensor types with incompatible channel spectral sensitivity curves

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