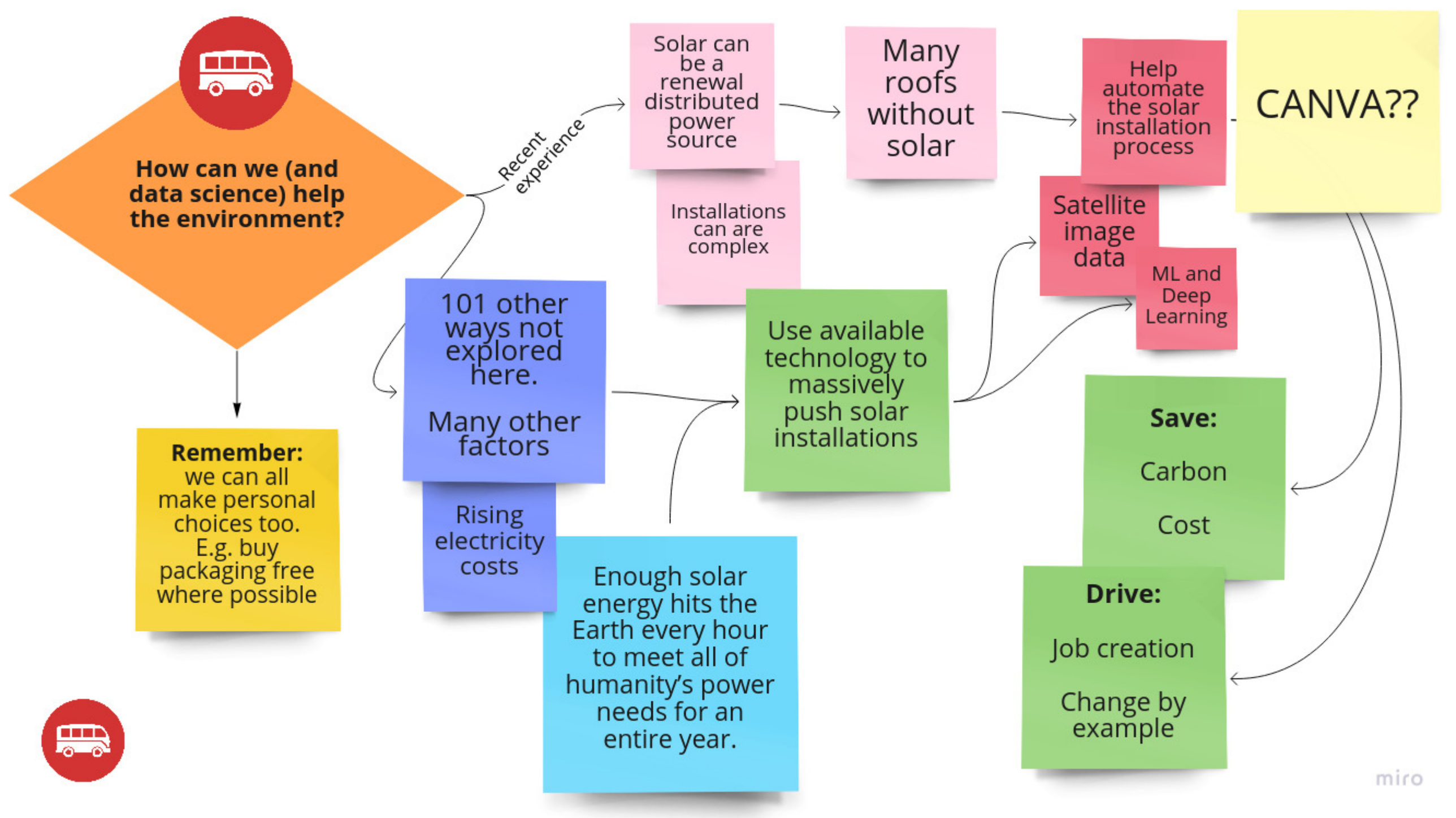
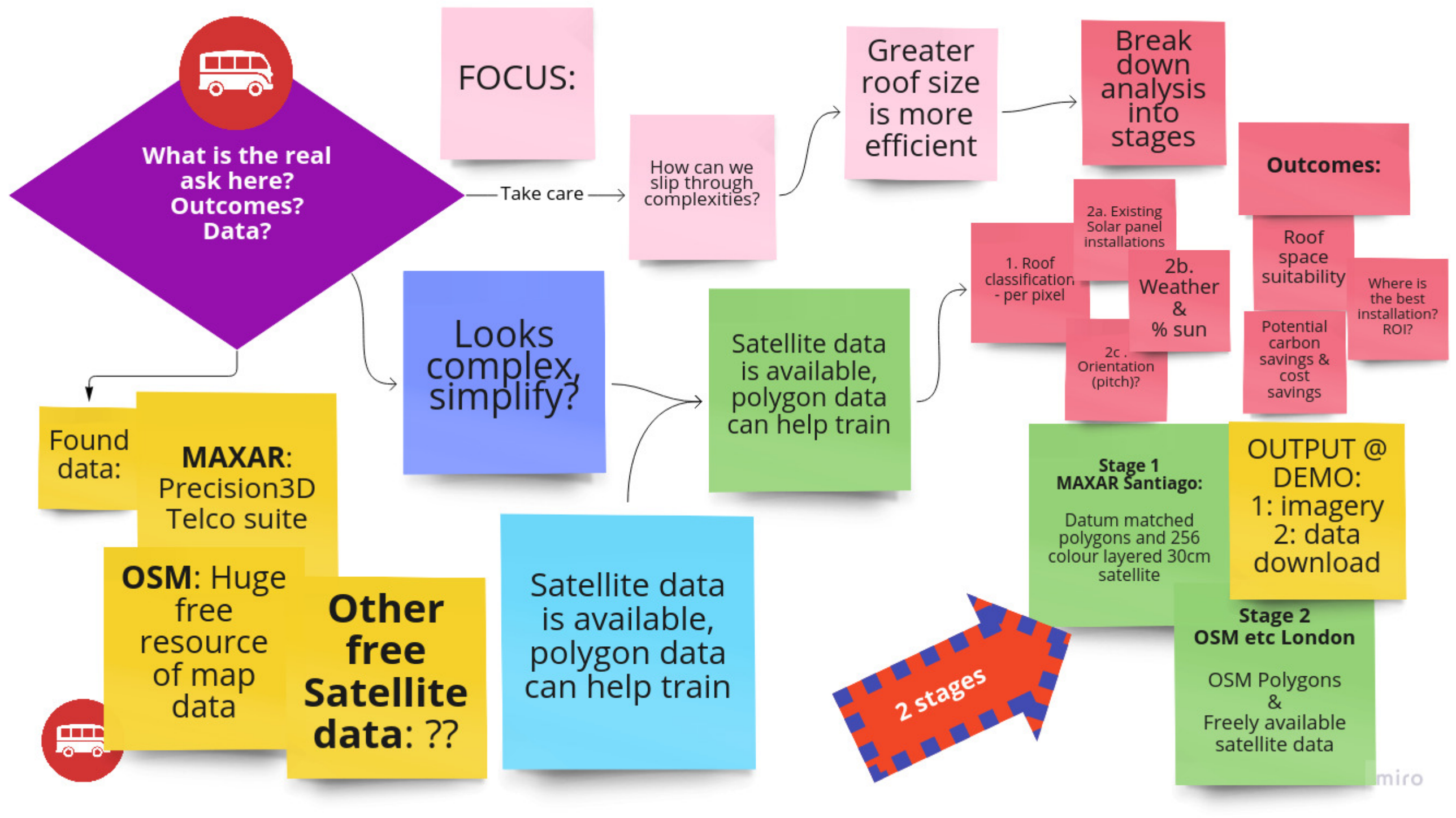

How can we (and data science) help the environment?
Recent experience
Solar can be a renewal distributed power source
Many roofs without solar
Help automate the solar installation process
CANVA??
Installations can are complex
Satellite image data
ML and Deep Learning
101 other ways not explored here.
Many other factors
Use available technology to massively push solar installations
Rising electricity costs
Enough solar energy hits the Earth every hour to meet all of humanity's power needs for an entire year.
Remember: we can all make personal choices too. E.g. buy packaging free where possible
Save:
Carbon
Cost
Drive:
Job creation
Change by example
miro


What is the real ask here? Outcomes? Data?
FOCUS:
Take care
How can we slip through complexities?
Greater roof size is more efficient
Break down analysis into stages
Looks complex, simplify?
Satellite data is available, polygon data can help train
1. Roof classification - per pixel
2a. Existing Solar panel installations
2b. Weather & % sun
2c . Orientation (pitch)?
Outcomes:
Roof space suitability
Where is the best installation? ROI?
Potential carbon savings & cost savings
Found data:
MAXAR: Precision3D Telco suite
OSM: Huge free resource of map data
Other free Satellite data: ??
Satellite data is available, polygon data can help train
Stage 1 MAXAR Santiago:
Datum matched polygons and 256 colour layered 30cm satellite
OUTPUT @ DEMO: 1: imagery 2: data download
2 stages
Stage 2 OSM etc London
OSM Polygons & Freely available satellite data
miro

What data?

data size

Found data:

MAXAR: Precision3D Telco suite

OSM: Huge free resource of map data

Other free data: ??

train on OSM cut outs

Train: LONDON boroughs

Validate: Santiago MAXAR?

data from a good paper?

test on Bristol

need research paper level labelled data to secure effectiveness

google earth engine - complex, but API earthengine.google.com

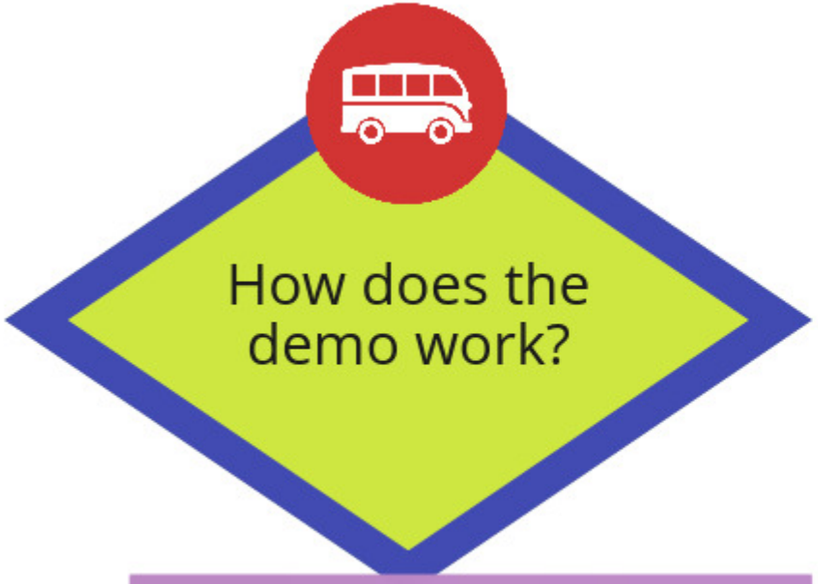
google scholar: image segmentation roof deep learning

Approach

Stage 1: Maxar or other specific well labelled data (tbc)

Stage 2
OSM etc London

OSM Polygons
&
Freely available satellite data



INPUT @ DEMO:
A: postcode area (e.g. se23)
OR
B: London borough

Heatmap: denser colour = better [solar ROI or larger roofs or etc]

OUTPUT @ DEMO:
1: imagery
&
2: data download

2a Potential carbon savings & cost saving

2b Where is the best installation? ROI?

1 Roof space suitability

Additional data on ROI or carbon saved etc if we have time

Cached pre-tested results if need be

Scaled live-processing if plausible

By postcode group (London)

London is an assumption for now!

2 Use Cases

By London Borough

And the model?

Metric

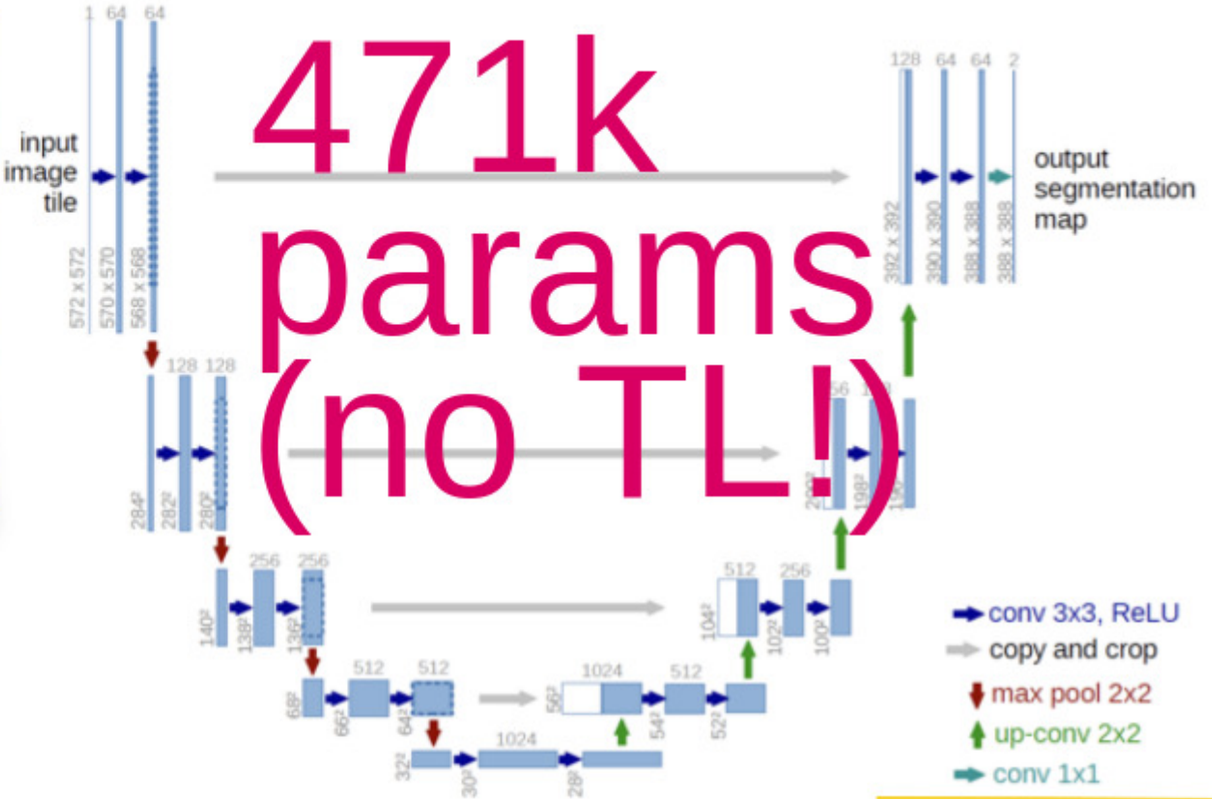
Model for segment: U-Net

IoU loss function

U-Net model

https://github.com/google/earthengine-api/blob/master/python/examples/ipynb/UNET_regression_demo.ipynb

471k params (no TL!)



Intersection over Union loss

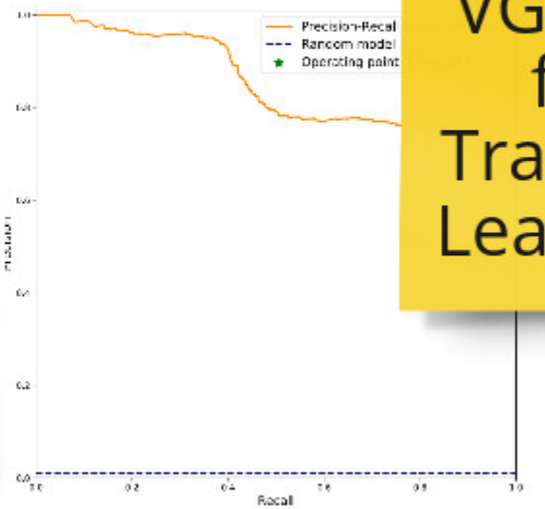
The accuracy metric can sometimes provide misleading results when the pixel class (PV) presence is small within the image, as the measure will be biased in mainly reporting how well the true negative cases (no-PV) are identified. A more suitable metric for image segmentation is the Intersection over Union (IoU), which consists of computing the common pixel area between the prediction and the ground-truth and dividing it by the area of union.

https://iopscience.iop.org/article/10.1088/1742-6596/1343/1/012034/meta

F1 on Precision-Recall curve

Figure 2 (right) also measures our final model skill in terms of Precision-Recall (PR) curve, more suitable than ROC curves for tasks exhibiting a large class imbalance, as in the case of our binary classification problem (PV vs no-PV pixels). Based on PR curve, we chose the probability threshold of the prediction array to be 95%, resulting in a F1 score (harmonic mean of precision and recall) of 0.8. This gives an IoU score of 0.64 and an accuracy of 0.94.

https://iopscience.iop.org/article/10.1088/1742-6596/1343/1/012034/meta



VGG-16 for Transfer Learning