

Big data, machine learning and maps: lessons learned on aerial imagery

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OS is known for

- ▶ **Accurate, authoritative data**

When it needs to be right

- ▶ **Trusted and respected worldwide**

A domestic focus with international reach

- ▶ **225 years experience**

The world's most experienced geospatial intelligence organisation.



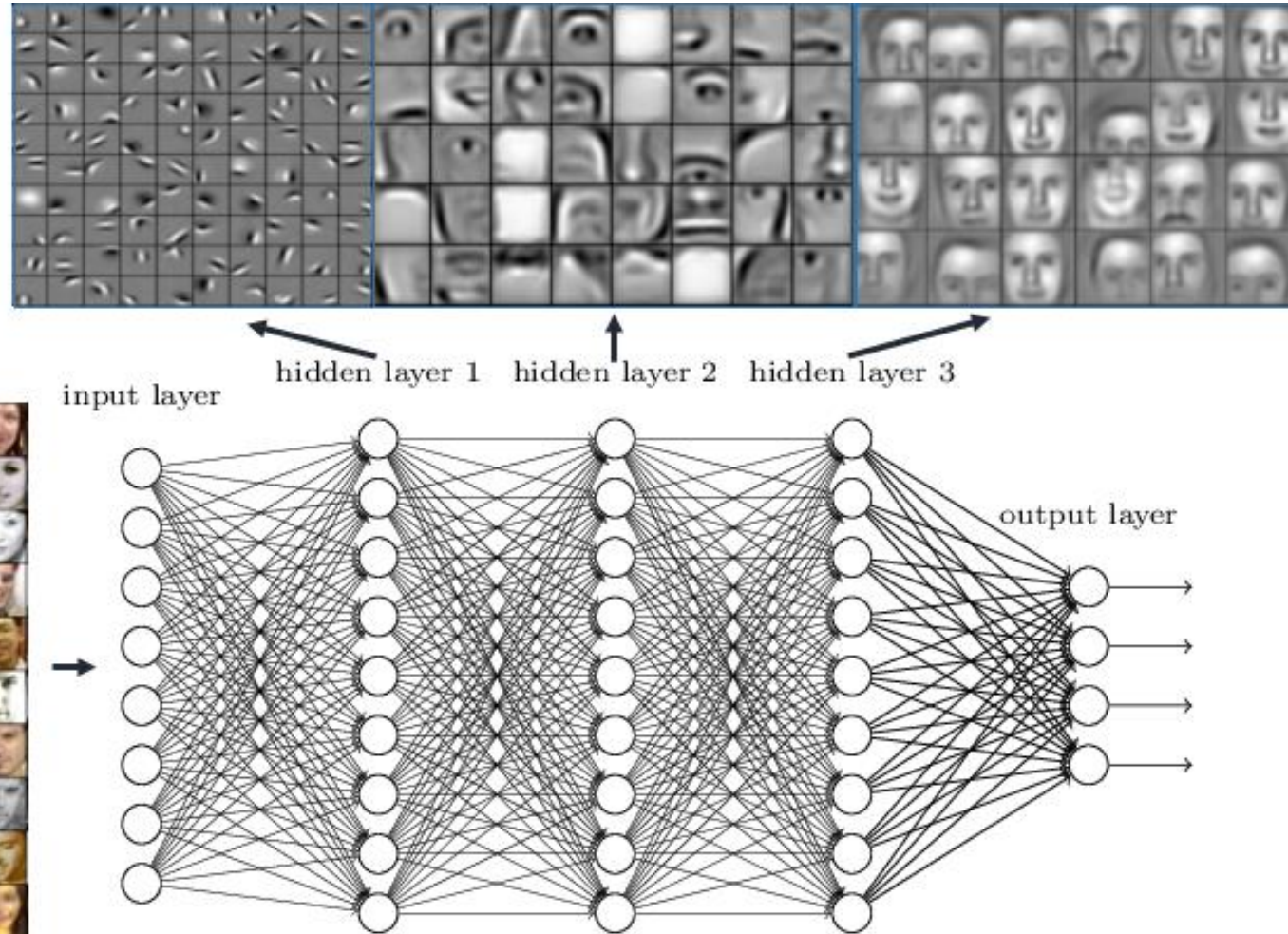
What OS actually does

- ▶ Paper maps now a legacy – less than 6% of our business but still hugely significant
- ▶ One of the UK's largest stores of geographic digital data
- ▶ Making **100,000+** updates every day to over **650+ million** physical features.



Convolutional Neural Networks (CNNs)

Deep neural networks learn hierarchical feature representations



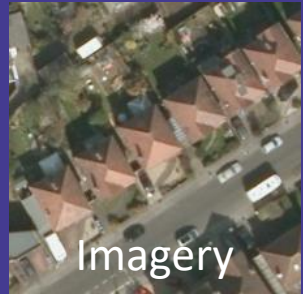
Learning deep representations

Convolutional
Neural Networks
(CNNs)

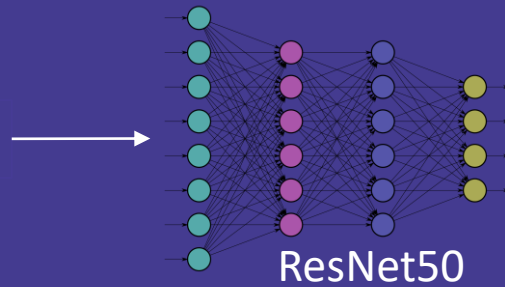
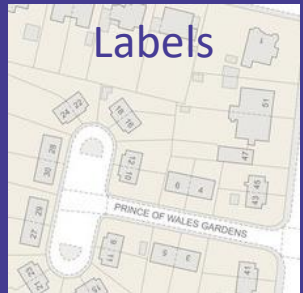
ImageNet



What are we doing?



Training Data



Training

TopoNet

TopoNet
Classes

Inference

New Data

Solar
Solar
Solar
Panel

Extracted
Features

Shallow
model

Transfer Learning

Solar Net

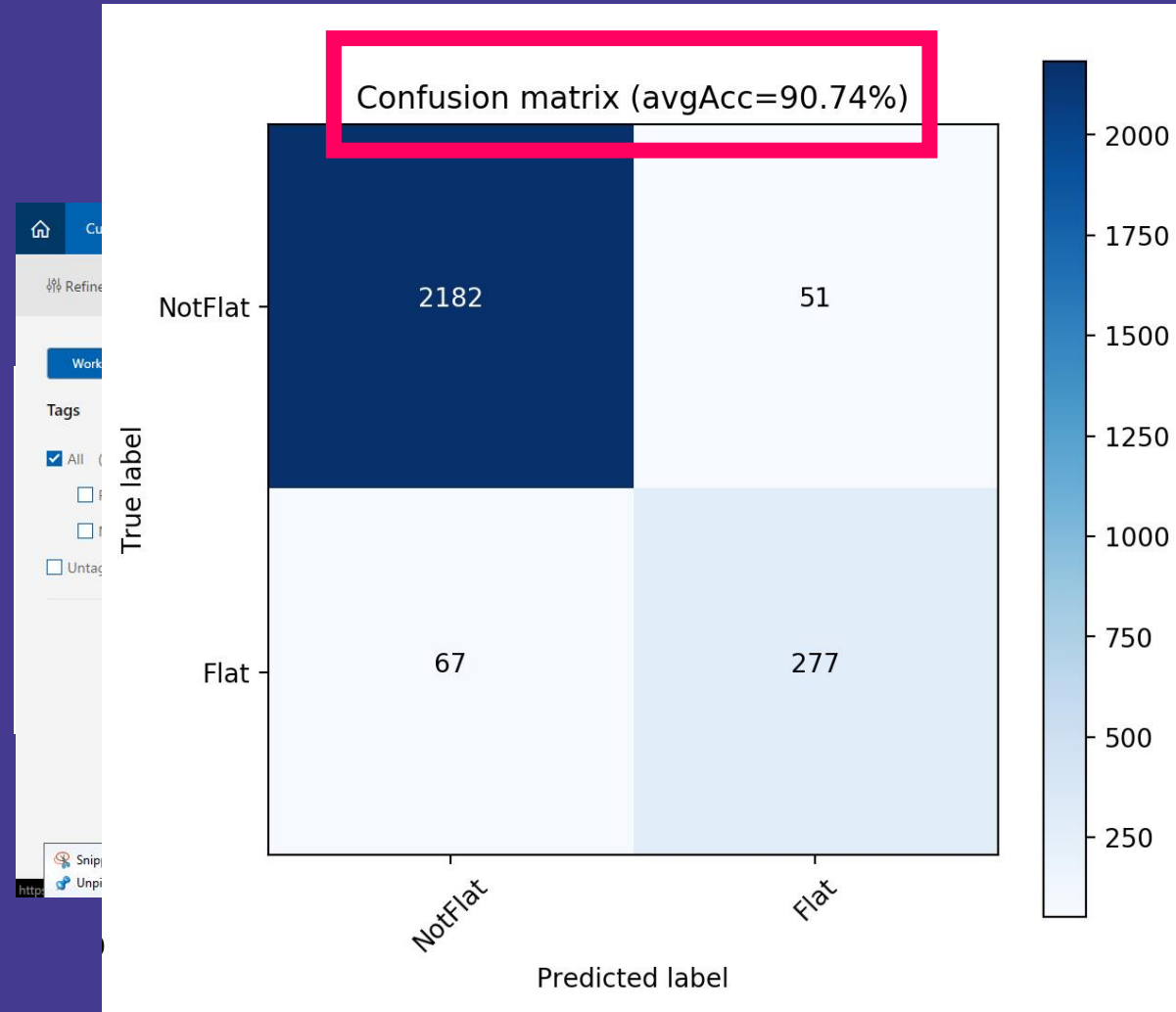
Solar

Not

Discovery

Microsoft Roof Hack

- ▶ 20,000 labels
- ▶ Only in Hull and Southampton
- ▶ Webservice creating an SVM using imagenet features
- ▶ ... but we weren't using equal classes

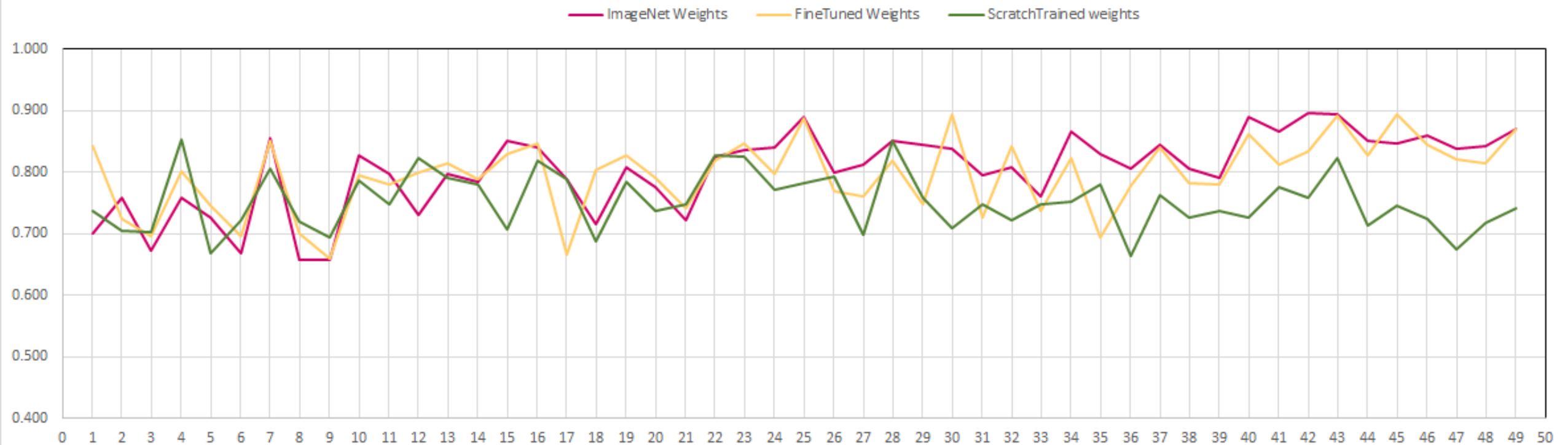


Training a CNN

- 1 GPU
- 50 layers ResNet50 architecture
- 1.2 million image-class pairs (Southampton area)
- Train from scratch with aerial imagery (“scratch train”)
- Steal the ImageNet weights (“imagenet”)
- Or, start with imagenet and then train using aerial imagery (“fine-tune”)

First Results of Transfer Learning

Accuracy of classifications of inference test data using features from different layers within trained ResNet 50



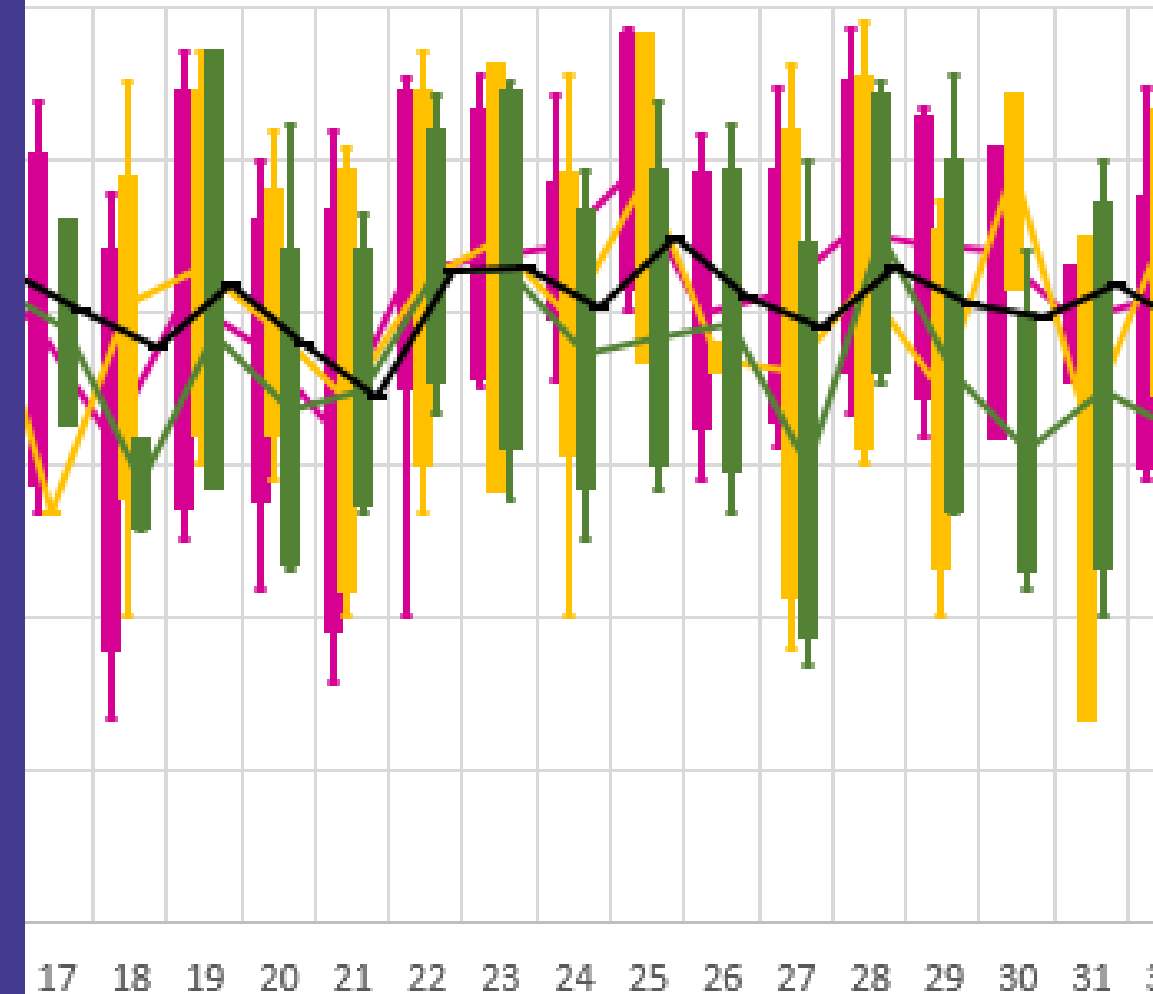
WHAT?

3 weeks to train (x 2)

Yet, at best AS GOOD AS ImageNet weights

reference test data using features from different

ImageNet Weights FineTuned Weights ScratchTrained weights



But...

Aerial imagery is different to ImageNet data because:

- ❖ No foreground/background relationship in the scene
- ❖ Not 'composed', e.g. with objects arranged in the middle
- ❖ Different colour and texture

So training with aerial imagery MUST be valid



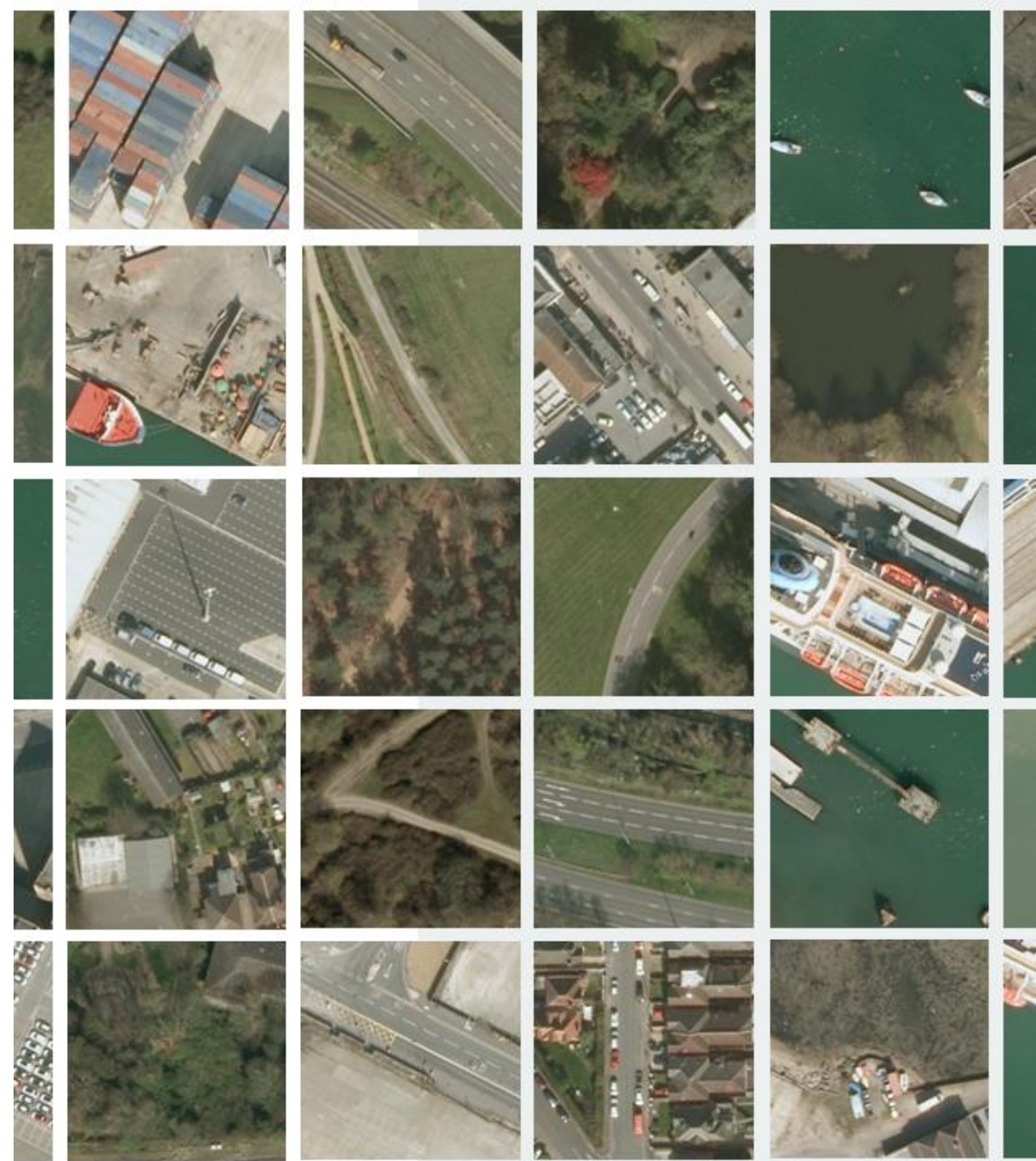
So...

We need to experiment to improve our model.
It's a many dimensional search space:

- Architecture
- Training time
- Hyperparameters

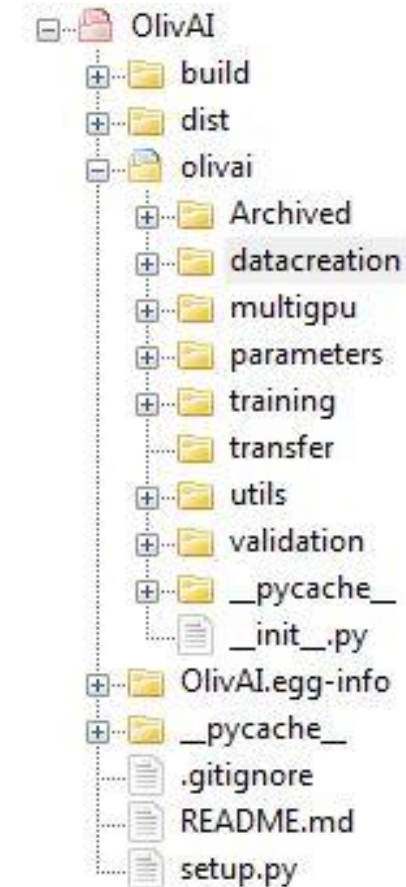
But...

3 weeks is too long



olivai

- ▶ 79 files
- ▶ ~ 3000 lines of code
- ▶ ~ 1200 lines of commenting (!)
- ▶ 'Olivia' → OlivAI

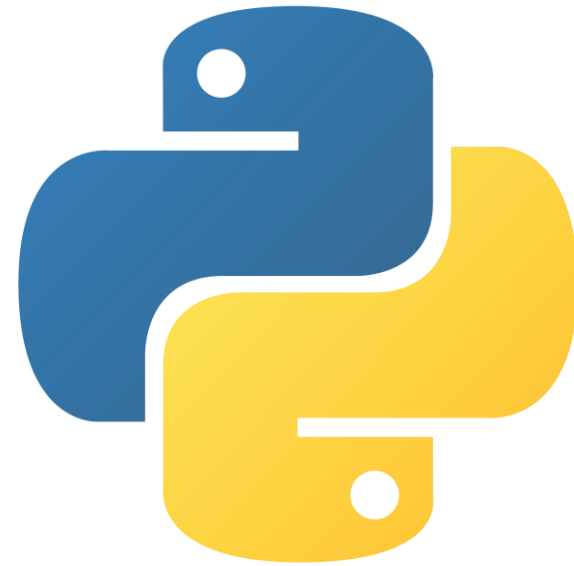
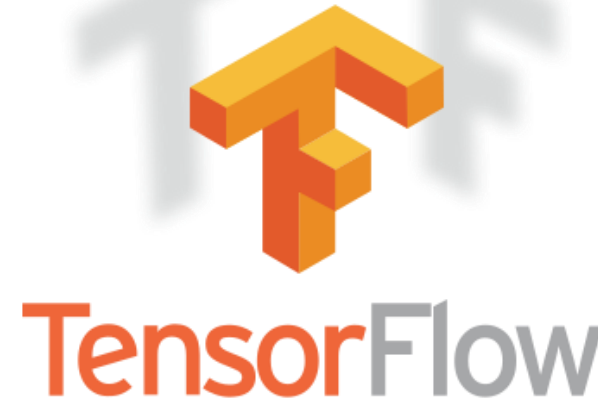


olivai

- ▶ Built on Python, TensorFlow and Keras

Why Keras?

- ▶ Well used and documented
- ▶ More seriously, multiple backends
- ▶ Easier than raw TensorFlow
- ▶ PyTorch was in its infancy when we started
- ▶ Better error handling than Neon



Running

```
from olivai.training import data_gen, train_on_gen  
args = parse_args()
```

```
# Create the generator for the data for the model to train on
```

```
gen = data_gen(args.folder, target_size=(224,224),  
               batch_size=args.batch_size)
```

```
serial_model = train_on_gen(args.arch, gen, args.batch_size,  
                             args.epochs, args.gpus,  
                             args.parameter_server,  
                             args.method, args.num_class)
```

Pipeline

```
def precompile(model_name, num_classes, gpus, parallel, epochs,
               run_test, batch_size, method,
               validation_data=None):
    (parallel_model, serial_model) = create_model(model_name,
                                                    num_classes,
                                                    gpus, method,
                                                    parallel)
    callbacks = default_callbacks(parallel, serial_model,
                                  batch_size)
    fit_dict = create_fit_dict(callbacks, epochs, run_test,
                               validation_data, parallel)
    return (parallel_model, serial_model, fit_dict)
```

Pipeline


```
def train_on_gen(model_name, gen, batch_size, epochs, gpu_count,
                 num_classes=12):
    out = precompile(model_name, num_classes, gpu_count,
                     epochs, batch_size, validation_data,
                     parallel=True)

    (parallel_model, serial_model, fit_dict) = out
    parallel_model.compile(**compile_dict)
    parallel_model.fit_generator(gen, **fit_dict)
    return serial_model
```


Parallelisation

- ▶ Parallelisation is hard!
- ▶ Data vs model parallelism?

What actually happens

- ▶ Create serial model (on CPU)
- ▶ Pass serial model to `make_parallel` ( `rossumai/keras-multi-gpu`)
- ▶ `make_parallel` distributes model onto GPUs
- ▶ When fitting the data batch (128 in my case) is divided between the GPUs (32 on each)
- ▶ On batch end each model comes back with different weights and updates them centrally

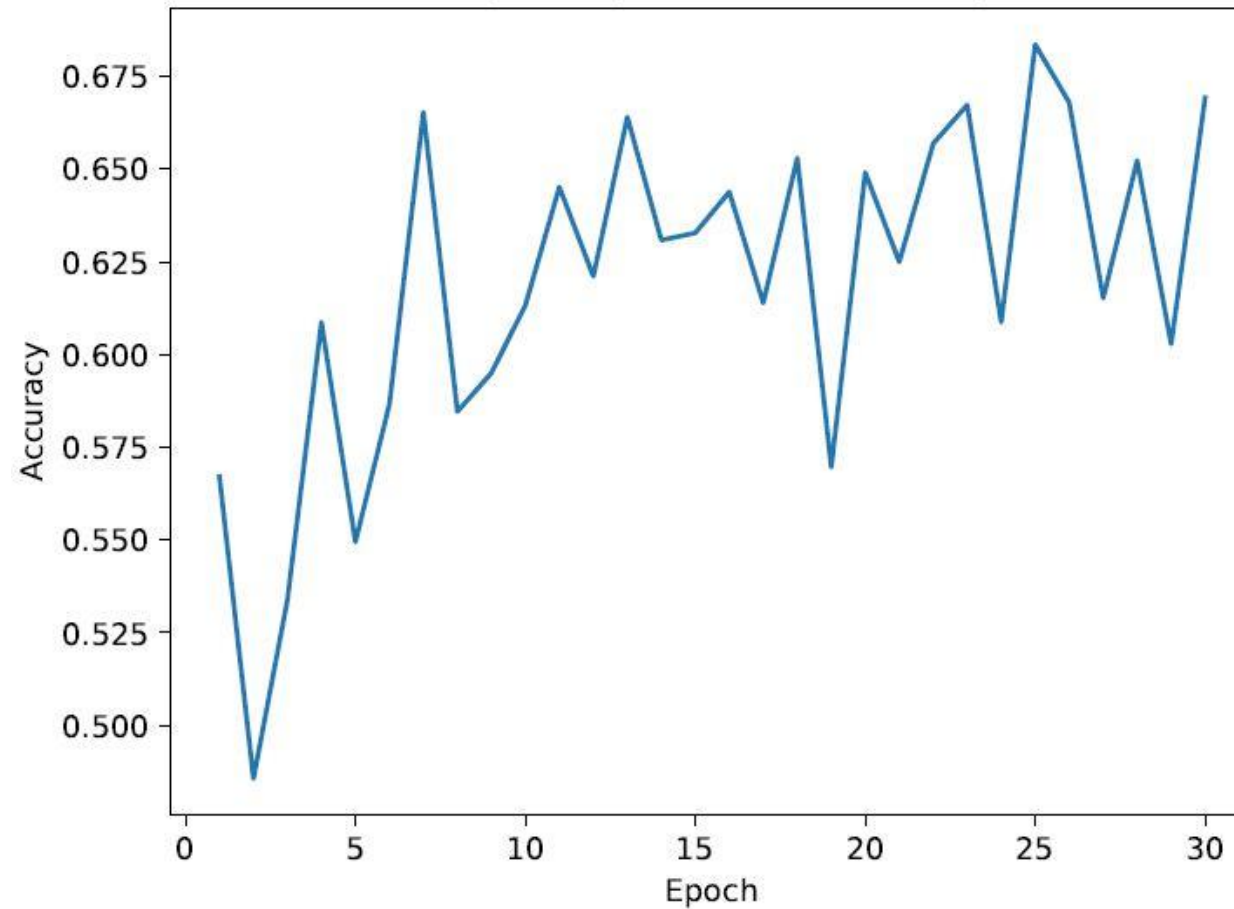
3 Weeks - > 2 days 😊

What decreased training time

- ▶ Parallelisation not using buggy parallelisation
- ▶ Also conda installs of keras and tensorflow (on keras > 2.2.2)

Results

Test accuracy of ResNet at each epoch



TopoNet V2

Speed ups mean we are able to iterate quickly

TopoNet is fully trained

We can iterate quickly

We can quickly change parameters

We have many to choose from

So which TopoNet is best for what task?



Transfer Learning

```
def create_feature_model(model, trained_weights, num_acts=None,
                        upper_layer=None):
    model.load_weights(trained_weights)
    acts = [l for l in model.layers if isinstance(l, keras.layers.Activation)]

    if upper_layer is not None:
        layer_names = [l.name for l in acts[:upper_layer + 1]]
    else:
        layer_names = [l.name for l in acts]

    outputs = [model.get_layer(layer).output for layer in layer_names]
    inp = model.get_input_at(0)

    feature_model = keras.Model(inputs=inp, outputs=outputs)
    return feature_model
```

Transfer Learning

```
def create_features(feature_model, folder, batch_size,
                    target_size):
    gen = data_gen(folder, target_size=target_size,
                   batch_size=batch_size)

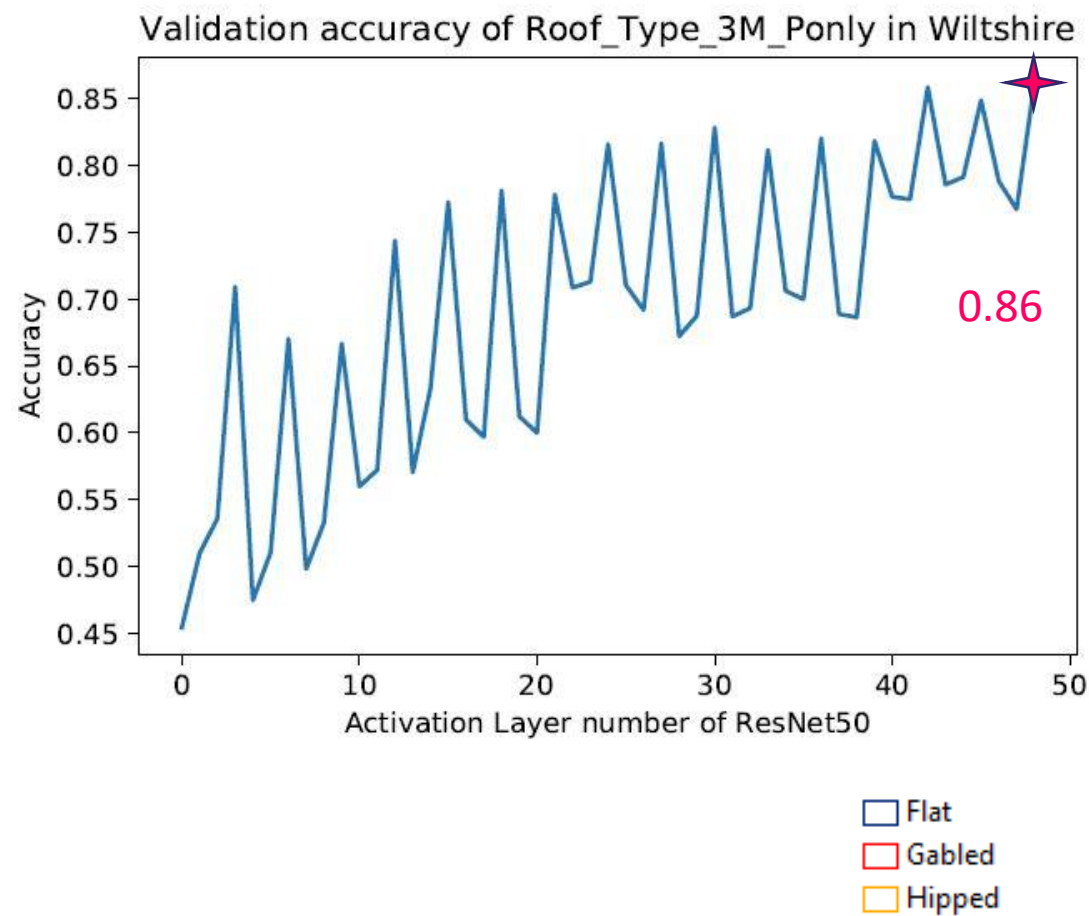
    features = feature_model.predict_generator(gen)

return features
```

- ▶ This returns a list of arrays for each layer of the network (chosen using `create_feature_model`)
- ▶ Each array is of shape `(num_images, num_filters, size_of_filters)`

So where are we now?

Complete
Class
Validated
Dipped
Attached
Tiled



Testing



```
cmd (Admin)

<1> cmd

(olivai) OWilson@afahpoc1w006 C:\OS_Code\OlivAI\tests
# pytest -m "not gputest"
===== test session starts =====
platform win32 -- Python 3.6.8, pytest-4.3.0, py-1.8.0, pluggy-0.9.0
rootdir: C:\OS_Code\OlivAI\tests, inifile: pytest.ini
collected 170 items / 30 deselected / 140 selected

test_parameters\test_parameters.py ..
test_training\test_callbacks.py ...
test_training\test_data.py .... FFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFF
FFFFFFFFFFFF [ 47%]
FFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFFF [ 77%]
test_training\test_model.py ..... [ 92%]
test_training\test_training.py ss [ 93%]
test_transfer\test_transfer.py sssss [ 97%]
test_utils\test_model_utils.py sss. [100%]

===== FAILURES =====
_____ test_shuffle_filenames[0] _____

seed = 0

    @pytest.mark.parametrize("seed",
                             range(100))
    def test_shuffle_filenames(seed):
>         list_fol, list_names, lookup_features = load_shuffle_jbls()

test_training\test_data.py:66:
-----
test_training\test_data.py:119: in load_shuffle_jbls
    list_fol, list_names = joblib.load(jbl_list)
```


Continuous Integration



Azure Pipelines

Open

Set up CI with Azure Pipelines #1

Update azure-pipelines.yml for Azure Pipelines

7f4f1dc

Add more commits by pushing to the **azure-pipelines** branch on **OrdnanceSurvey/OlivAI**.

Some checks haven't completed yet

2 pending checks

OrdnanceSurvey.OlivAI

Pending — in progress

Details

sensed-data-CI

Pending — in progress

Details

This branch has no conflicts with the base branch

Merging can be performed automatically.

Merge pull request

You can also [open this in GitHub Desktop](#) or view [command line instructions](#).

Write

Preview

AA B i “ < > ↻ ⋮ ⋮ ⋮ @ 🚩 ↶

Leave a comment

Attach files by dragging & dropping, selecting them, or pasting from the clipboard.

Styling with Markdown is supported

Close pull request

Comment

Opened by owilson-os

Projects

None yet

Milestone

No milestone

Notifications

Unsubscribe

You're receiving notifications because you authored the thread.

1 participant

Lock conversation

Edit

Queue

Build #

20190306.1

20190218.2

20190218.1

20190206.10

20190206.8

20190206.7

20190206.6

ProTip! Add comments to specific lines under [Files changed](#).



Conclusions

- Developed a robust python library (**olivai**) with documentation, testing and continuous integration with necessary functionality.
- Data remains '90%' of the work, and probably always will (long live the domain expert)
- We can now iterate quickly; essential to our work
- We've trained some deep networks and are now in a position to train in anger rather than mild frustration

Any Questions?

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