# MORPHOLOGY READOUT - EXTENDED

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# EXECUTIVE SUMMARY

Following up the previous project, GAIA investigated how we can enhance efficiency of labeling GE images from a relatively few experts while reducing inter-labeler subjectivity, including auto-labeling

- Duration: 8 weeks (11 JUN – 9 AUG)

Achievements:

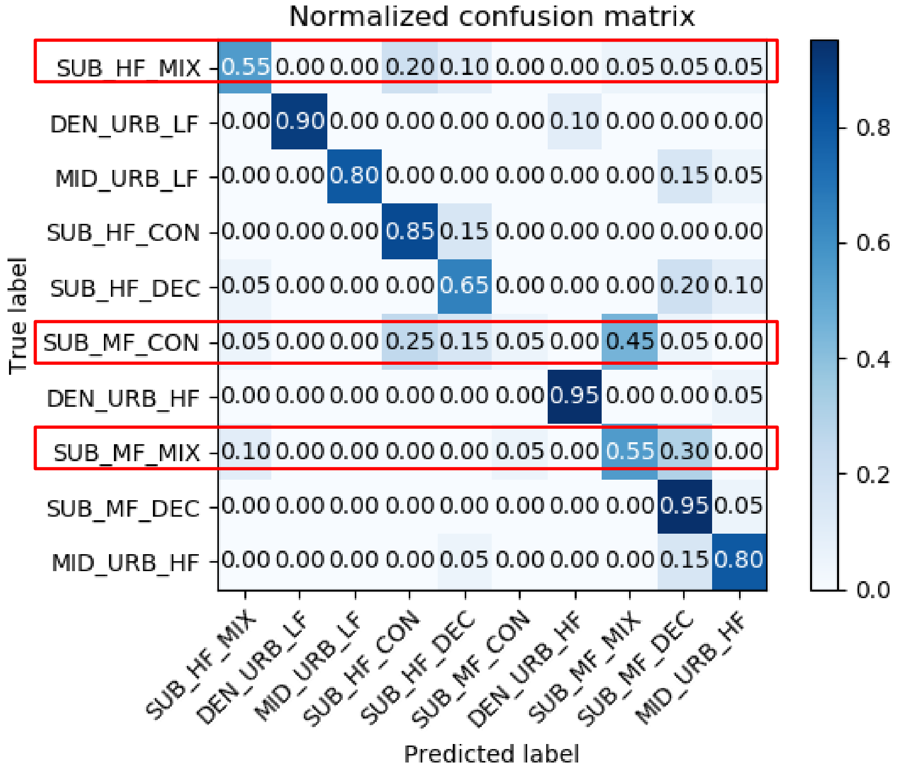
- Proved that the task of labeling is hard to distribute: Need to reduce subjectivity further.
- 3D augmentation increases accuracy by 2%
- An MVP of single-attribute auto-labeler showing enhancement by freeing system from inter-labeler variance.

GAIA agree with Miro's proposal of:

- Flexible class definition by combining three(or more) single-attribute classifiers, which will be more flexible to cope with dynamic requirements from external customers.

# LESSON: LABELING IS NOT EASY TO DISTRIBUTE

- GAIA expected the common set (453 labels which were unanimously agreed among Rina, Space, and Eric) to be additive to Miro's set in spite of its low yield rate (28%).
- However, GAIA found that performance **degraded** from 0.82 to 0.68 when used a <u>Miro+Common set for training</u>



# HOW FAR THE COMMON SET IS FROM MIRO'S?

On the common set, GAIA predicted classes from a Xception net which used Miro's dataset for training (aka, simulated "Miro's mind") and measured similarity with human labels from Canada set.

- Used 4-fold CV for avoiding sample bias: performance is intentionally unoptimized for saving time.
- For all labelers, similarities were consistently low across labelers: 0.52-0.59
- Only Common set was relatively close (0.71) to "Miro's mind"

| | RINA | ERIC | SPACE | COMMON | MIRO |
|---|---|---|---|---|---|
| **Fold 1** | 0.5244 | 0.5817 | 0.5610 | 0.6909 | 0.7993 |
| **Fold 2** | 0.4982 | 0.6135 | 0.6017 | 0.7727 | 0.7616 |
| **Fold 3** | 0.5438 | 0.5720 | 0.5364 | 0.6636 | 0.7777 |
| **Fold 4** | 0.5035 | 0.5904 | 0.5643 | 0.7222 | 0.7788 |
| **Average** | 0.5174 | 0.5894 | 0.5659 | 0.71235 | 0.7794 |

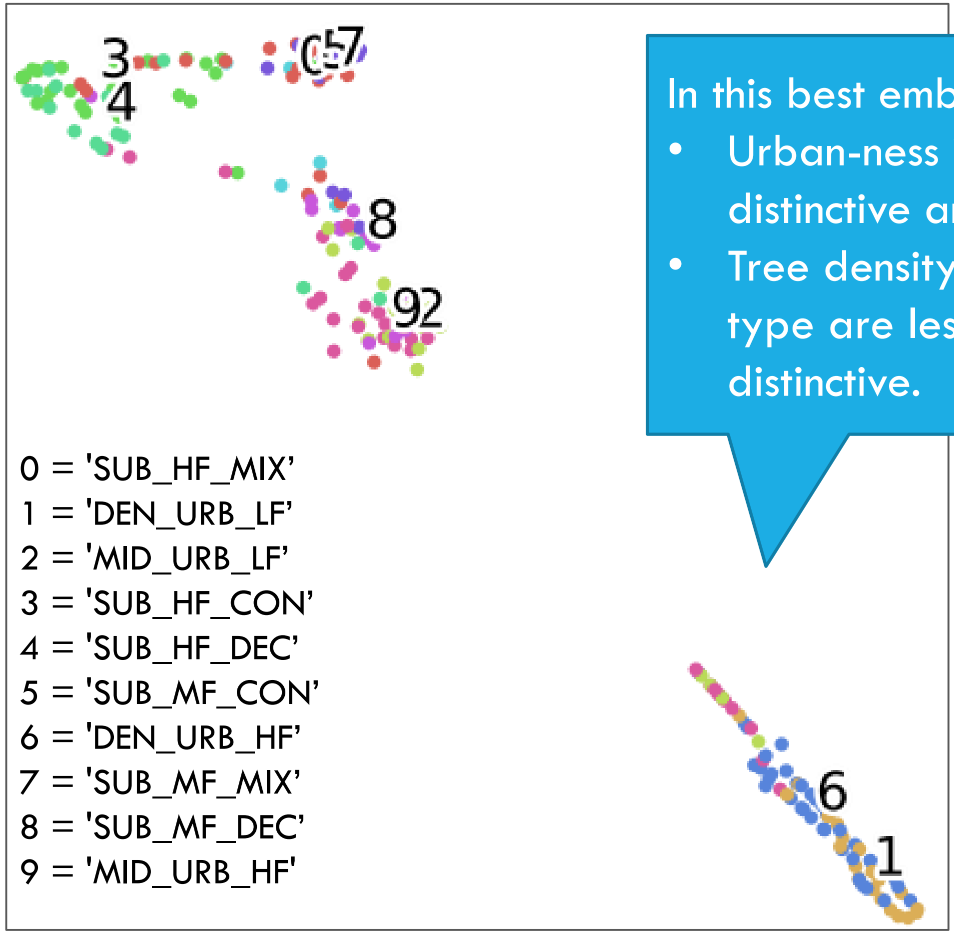
Maximum test score only in this setting

**Common set is still valid as a standalone training set: But, do not mix up Miro's set.**

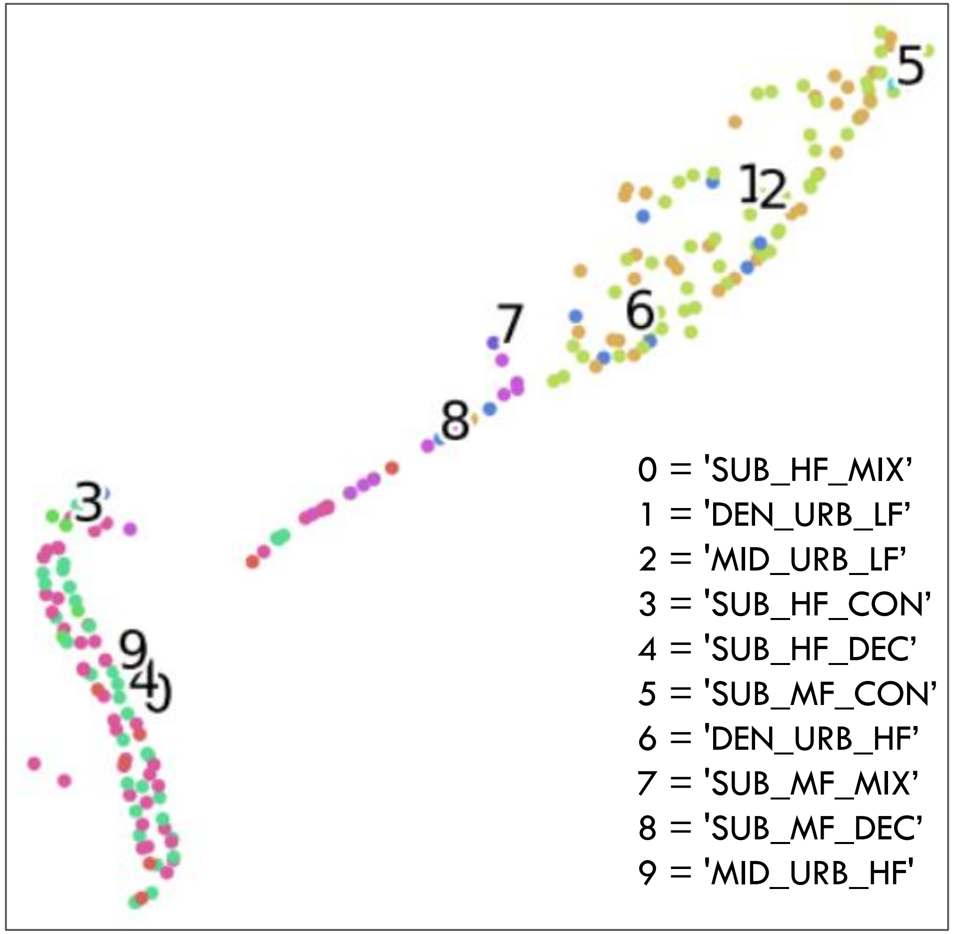
# T-SNE RESULTS FROM TWO LABELER GROUPS

In this best embedding,

- Urban-ness is most distinctive and easy
- Tree density and type are less distinctive.

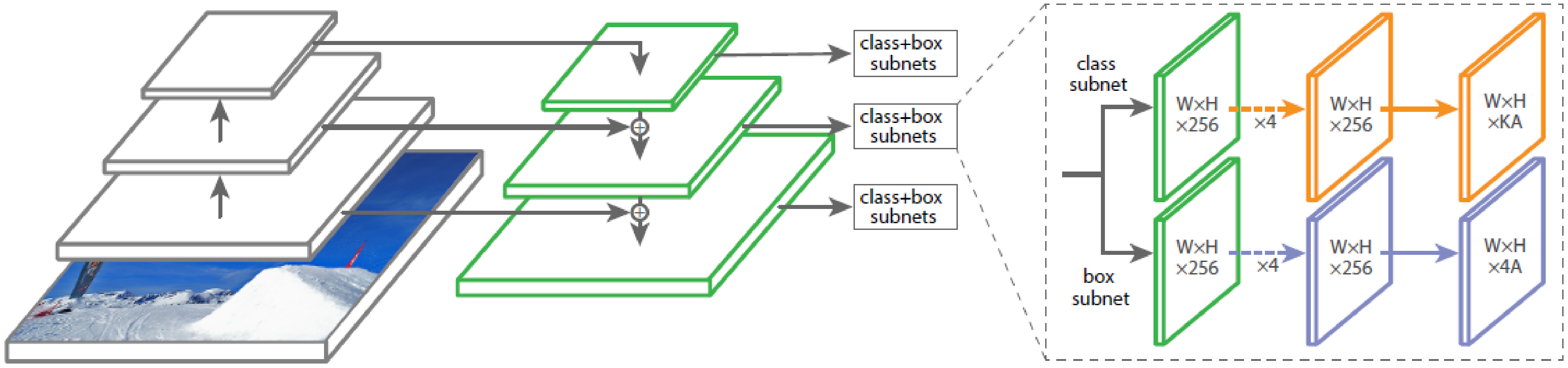



Miro's dataset




The common dataset

# THEN HOW TO AUTOLABEL TREES?

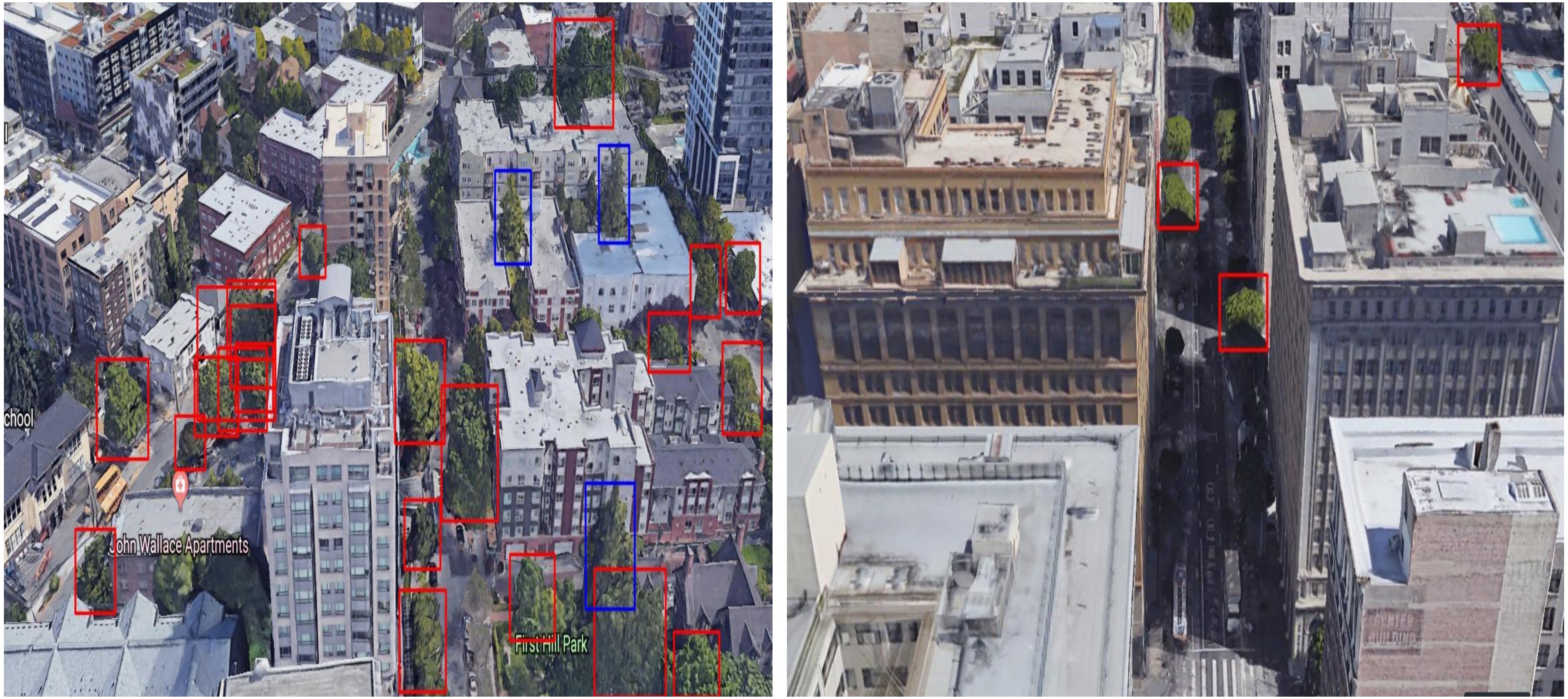



**Objective:** To find CON and DEC trees in a given scene.

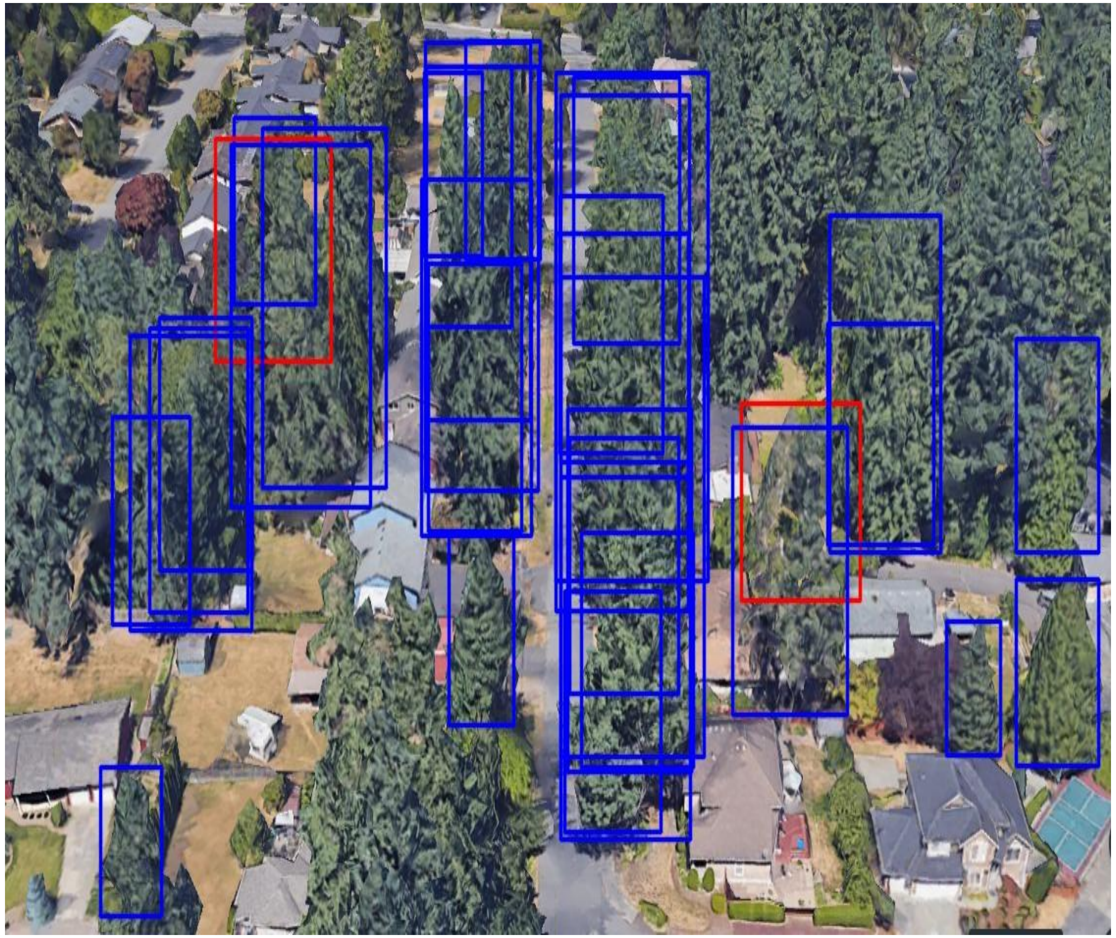
## Approach:

- RetinaNet with ResNet50 backbone finds CON and DEC trees.
- Trained on around 6000 US images of trees.
- The second CNN model crosscheck if that is a tree image. Trained on 2000 trees and 2000 building US images.

# TREE COUNTER: URBAN RESULTS (US)



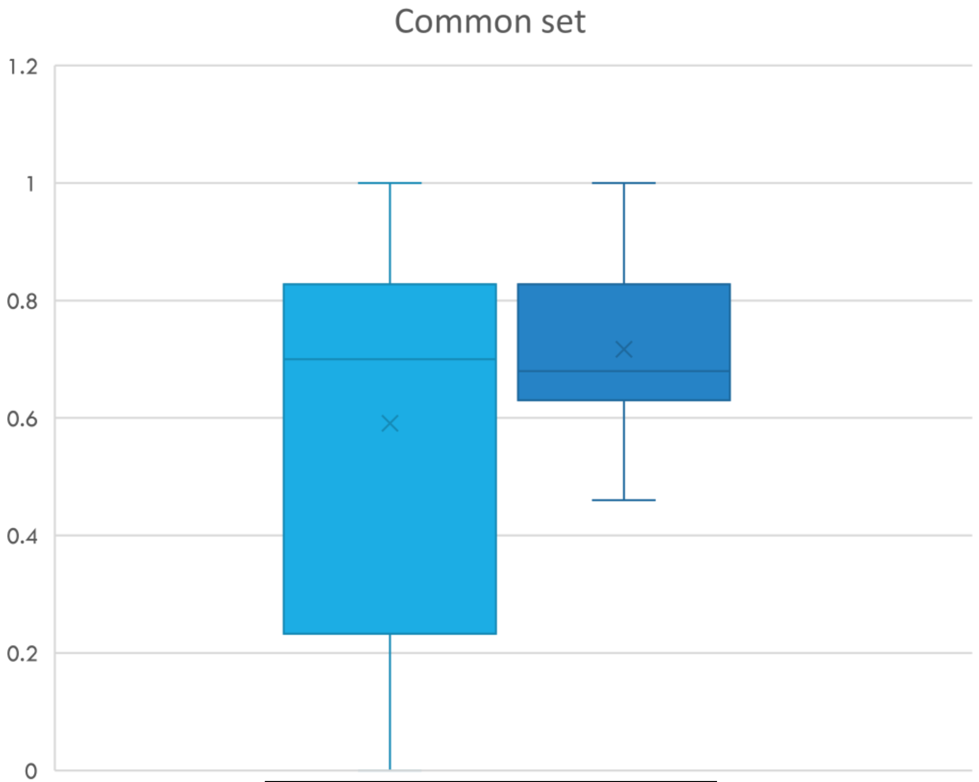
# TREE COUNTER: SUBURB RESULTS (US)

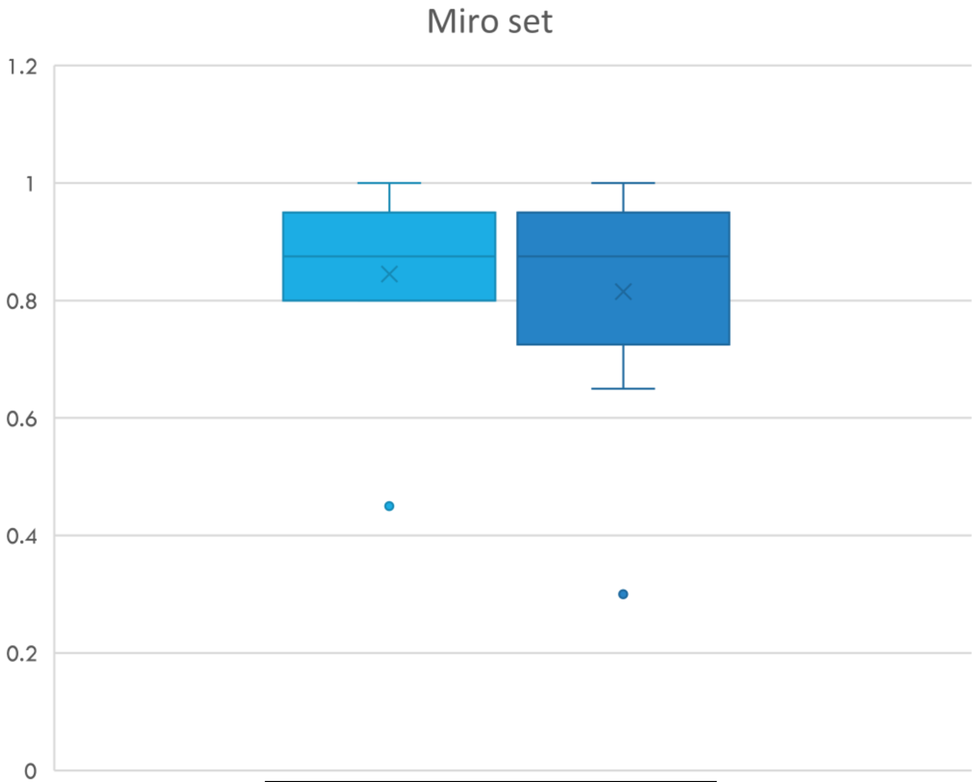
# TREE COUNTER: RESULT IN COMMON CANADA SET

# TREE COUNTER: BEFORE-AND-AFTER

It enhanced learnability significantly when there is a inter-labeler ambiguity.



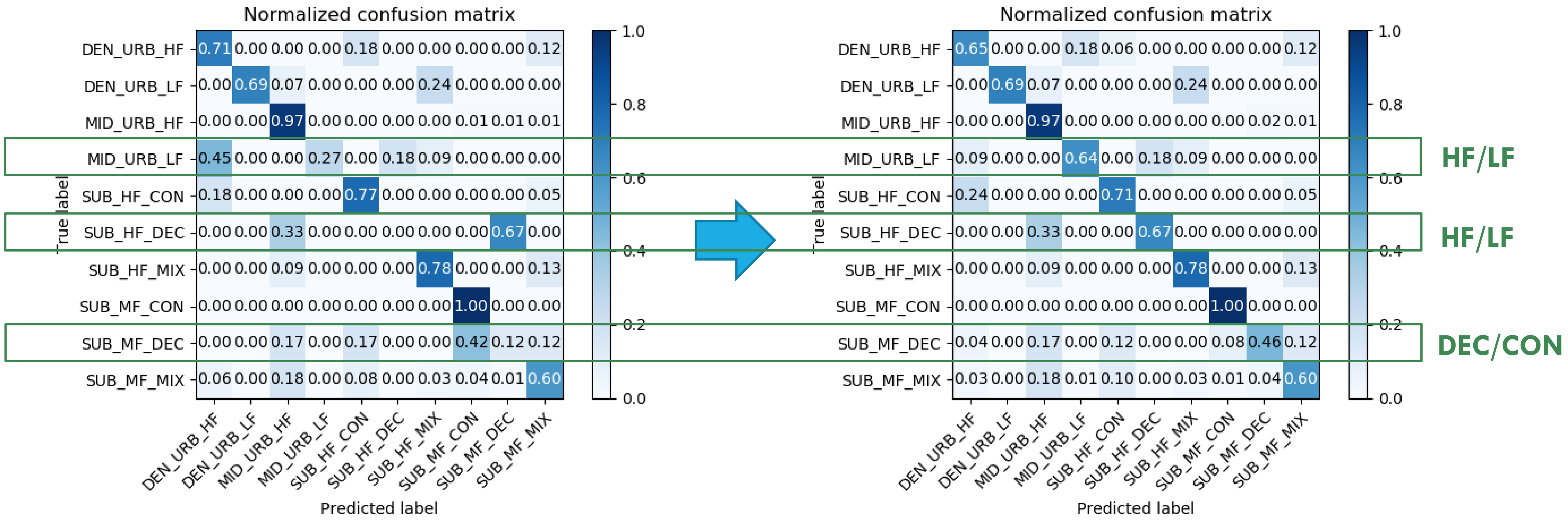

| | before | after |
|---|---|---|
| mean | 0.59 | 0.72 |
| std | 0.35 | 0.16 |




| | before | after |
|---|---|---|
| mean | 0.85 | 0.82 |
| std | 0.16 | 0.21 |

# TREE COUNTER: WHICH CLASSES ARE ENHANCED

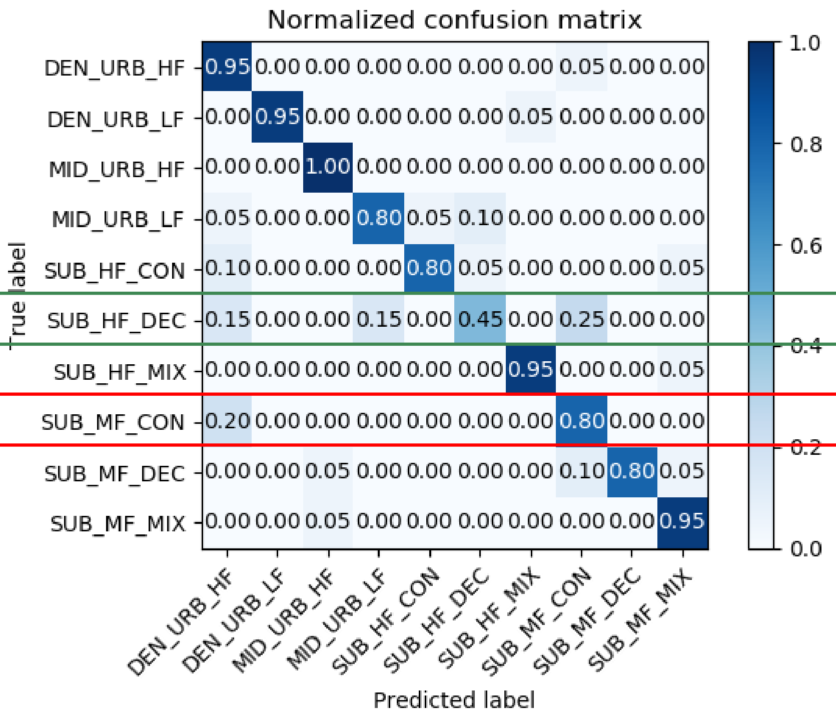
Three classes are hugely benefitted while two classes slightly degraded.



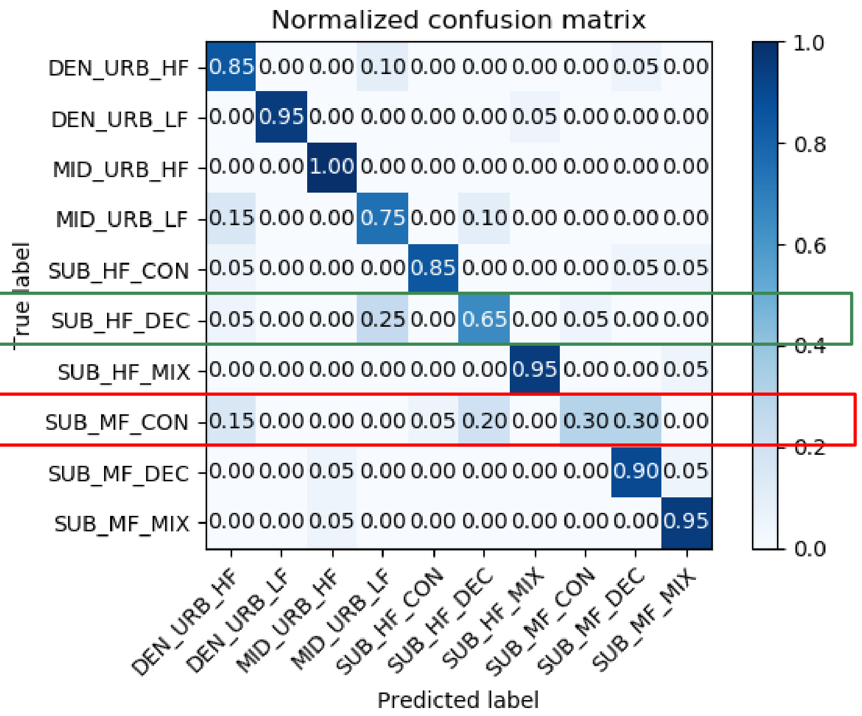

**Before** **After**

The Common Set

SUB_HF_DEC is enhanced while SUB_MF_CON goes wrong by some reason.




**Before**




HF/MF, CON/DEC

CON/DEC

**After**

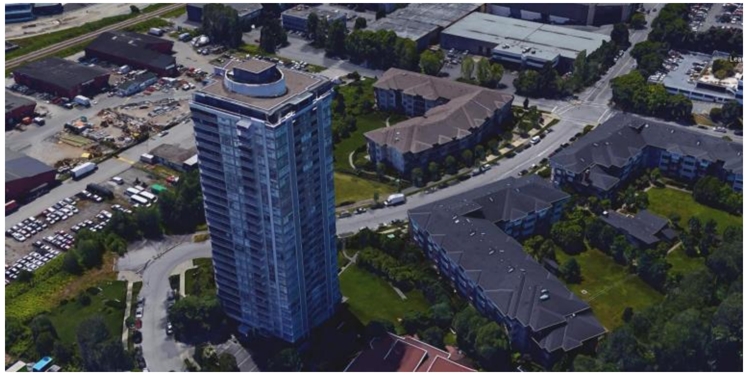
Miro’s Set

# 3D AUGMENTATION: 2% INCREASE IN ACC.

Step size: 0.5 degree in azimuth, 1.0 degree in tilting

Range: [-1.5, +1.5] in azimuth, [-1.,+1] in tilting: 7*3 = 21 times more data

+1



-0.5

0

+0.5

-1

# SUMMARY

## Conclusion

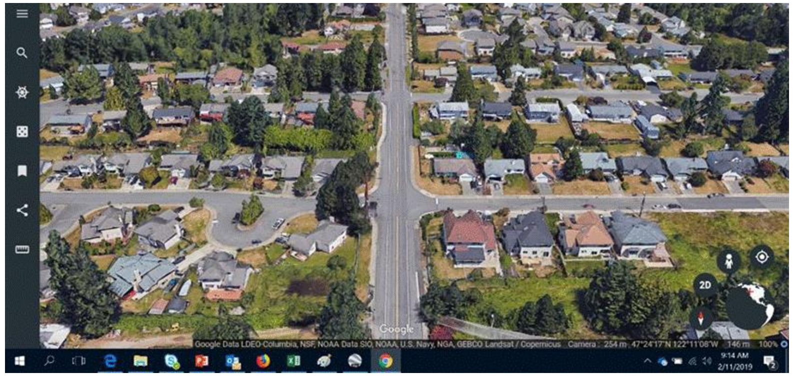
- Till now, Miro's set is the only reliable source to use.
- Tree detector/classifier can be useful for compensating the weakest part from the view of human labeling
- We can reuse the current Xception net as an urban-ness classifier with high accuracy (>0.9)
- Whenever Miro creates the next "golden" dataset, we recommend to preserve lat/long/heading for using 3D augmentation later. That will allow us 21x or more amplification in dataset.

## Future Works (If we extend this project)

- To enhance performance of a tree detector/classifier
- To test the idea of combinational class redefinition system

# MORPHOLOGY ACCEPTANCE CRITERIA DATE: 20190729

# MORPHOLOGY SOLUTION



Solution

- GAIA release targeted for July 31
- Includes Tree counter for automatically labeling tree type—and hopefully tree density

Exclusion

- New requirements in definition—e.g. requirements from AT&T for more than 10 classes

Input

- List of site s with details of name/id, lat/long, azimuth,

Output

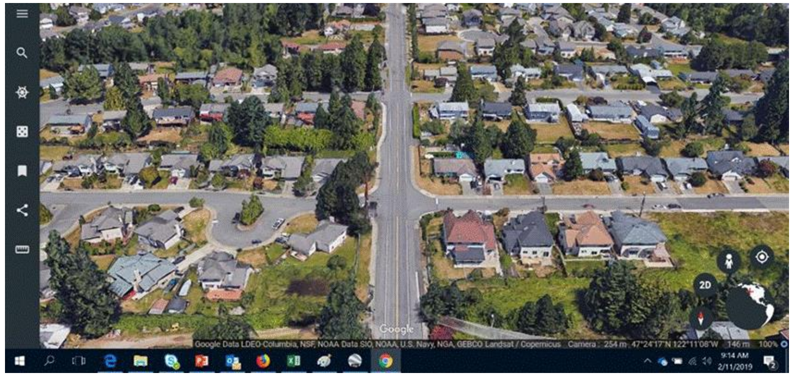
- Captured picture
- One of 10 classifications

| | |
|---|---|
| — Dense Urban with medium to high foliage, (a.k.a. DEN_URB_HF) | CLASS 0 |
| — Dense Urban with little to no foliage, (a.k.a. DEN_URB_LF) | CLASS 1 |
| — Urban with medium to high foliage, (a.k.a. MID_URB_HF) | CLASS 2 |
| — Urban with little to no foliage, (a.k.a. MID_URB_LF) | CLASS 3 |
| — Suburban, high foliage density, mostly coniferous (a.k.a. SUB_HF_CON) | CLASS 4 |
| — Suburban, high foliage density, mostly deciduous (a.k.a. SUB_HF_DEC) | CLASS 5 |
| — Suburban, high foliage density, mixed coniferous and deciduous (a.k.a. SUB_HF_MIX) | CLASS 6 |
| — Suburban, medium foliage density, mostly coniferous (a.k.a. SUB_MF_CON) | CLASS 7 |
| — Suburban, medium foliage density, mostly deciduous (a.k.a. SUB_MF_DEC) | CLASS 8 |
| — Suburban, medium foliage density, mixed coniferous and deciduous (a.k.a. SUB_MF_MIX) | CLASS 9 |

# MORPHOLOGY SOLUTION – ADDITIONAL DETAILS

GAIA is making the tree type labeler using Retinanet. We can utilize the labeler as following:

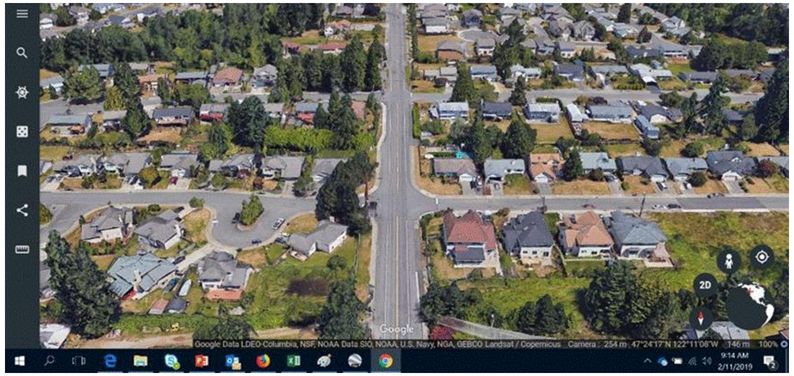
1. Conservative usage: You can use the labeler for correcting the DEC/CON/MIX labels in human-labeled set. For a given labeled image as an example, if we detect discrepancy among human labelers (e.g., SUB_HF_DEC, SUB_HF_CON, SUB_HF_MIX) about the image, you run our tree type labeler with the result of "DEC" and finalize its label as SUB_HF_DEC by substituting the tree type by ML-based decision.
2. Aggressive usage: We can use the tree type labeler for compensating the SEAL and thereby generate more labeled images automatically for your future work. Because the current SEAL is trained using the ambiguous labels, we will retrain SEAL, check the changed nature, and then combine with the tree type labeler.



# MORPHOLOGY SOLUTION – ACCEPTANCE CRITERIA

**Acceptance Criteria:**

- Classification accuracy 90+%
- Note: Ericsson SMEs accept the automated tree type labeling and/or GAIA's proposal including stacking of Xception nets and 3D augmentation as the approach




**Notes:**

- The 10 classes can be described as the combination of 3 factors: urban-ness(DEN_URB/MID_URB/SUB), tree density(HF/LF), and tree type(DEC/CON/MIX).
- Human labelers mutually agree on urban-ness really well and so does ML while tree density is relatively ok. Most discrepancy happens in tree type for both(humans and ML).