Leaf Counting and Area Estimation using 3D Point Cloud Data

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Problem

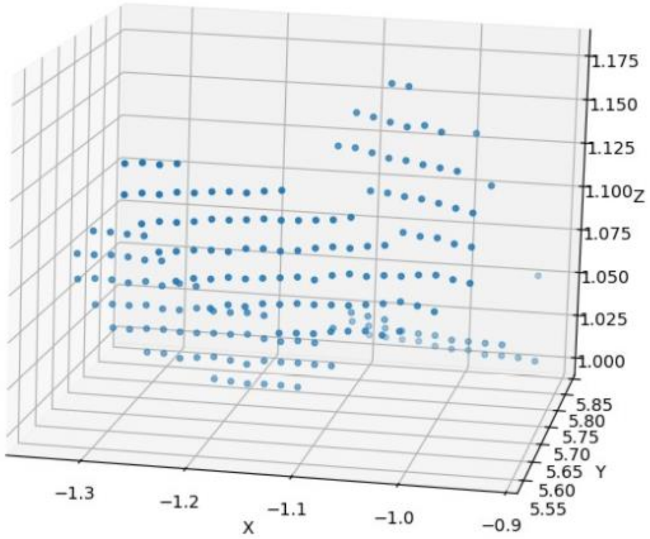
- Goal: Estimate total leaf area and number of leaves from lidar point cloud.
  - Input: 3D point cloud measured from lidar at position [0, 0, 1.5].
  - Lidar records only the closest object along each beam.
  - Points may correspond to leaves, branches, trunk, or ground.
  - Assume no obstacles between lidar and measured points.
  - Task: Use modelling to compute leaf area and estimate leaf count.
  - Also assess accuracy and reliability of chosen methods.
  - Data simulated using HELIOS++ (Winiwarter et al., 2022).

Agenda

- Problem description
- Assumptions made
- Model
  - Leaf identification
  - Objective function
- Model Optimization
  - DBSCAN
  - RANSAC
- Evaluation
  - Visual inspection
  - Simulated data
- Final estimation
- Conclusion

Assumptions

1. **Point Density:** The point cloud density is adequate to capture the essential structure of the leaves. Its resolution is finer than the most leaves' size.
2. **Leaf Shape:** Leaves are mostly planar and can be approximated as flat surfaces.
3. **Environmental Conditions:** The data was obtained in still air conditions, minimizing motion blur or distortion in the point cloud.



Model – Leaf Identification

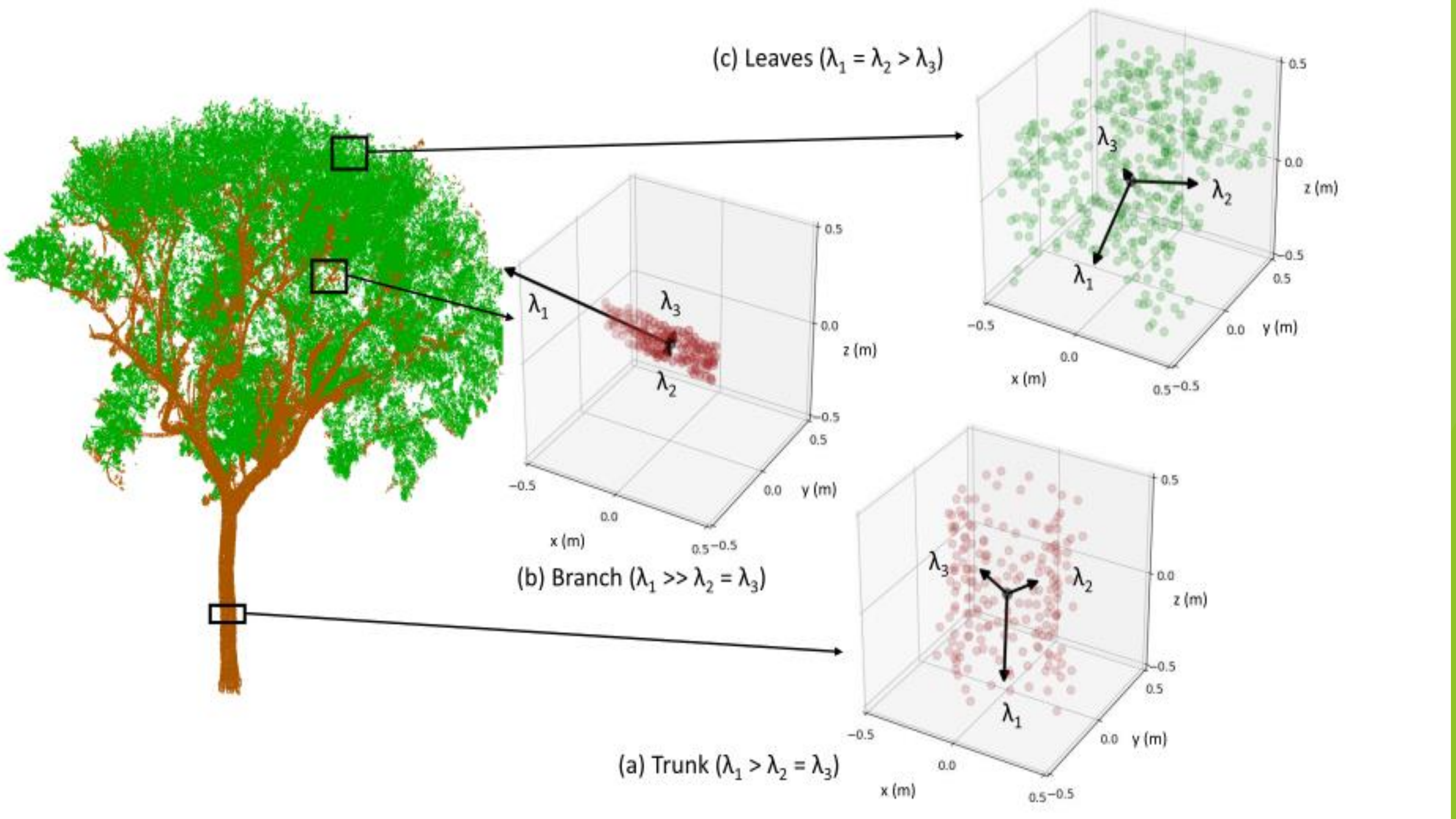
Planarity: Leaf
points approximately form a flat
surface.

Separability & Density:
clusters separated by sparse
regions.

Leaf Size: Cluster area and
dimensions within leaf-size limits.

function **is_leaf_cluster**(*points*)

1. planarity via **PCA**(*points*)
2. all *points* lies in a plane
3. *#points* within some range
4. **return** TRUE if satisfy all



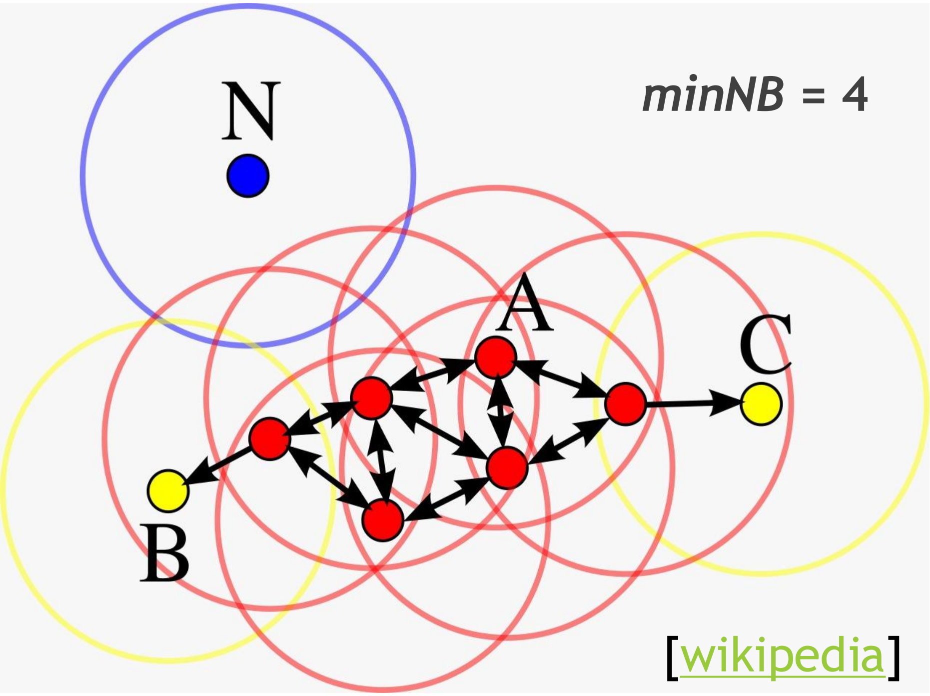
[Moorthy et al, 2020]

Model – Objective function

- **Goal:** Evaluate how well a clustering separates leaf-like point clusters while avoiding over-segmentation.
- Scoring rule for the leaf-like clusters (score_function):
  - Score = **sum of (number of points in each leaf-like cluster)^2**
  - Encourages **large, coherent leaf clusters**
  - Penalizes splitting a single leaf into many small clusters
  - Integrates leaf-likeness (semantic + instance segmentation)
- Objective function optimization was done by simple exhaustive search for different hyperparameters and clustering methods.

Model – Tools

DBSCAN: Density based clustering

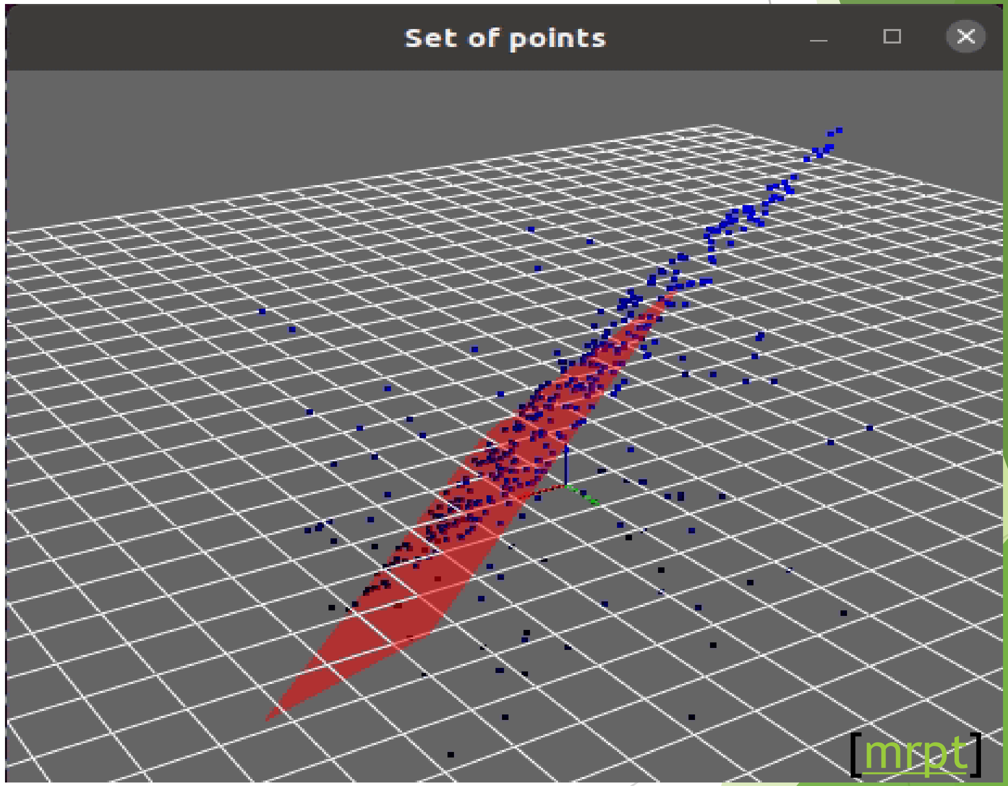


red (A): core points, #NB≥4 (included)

yellow (B,C): neighbour of a core (included)

blue (N): no core neighbour, #NB<4 (excluded)

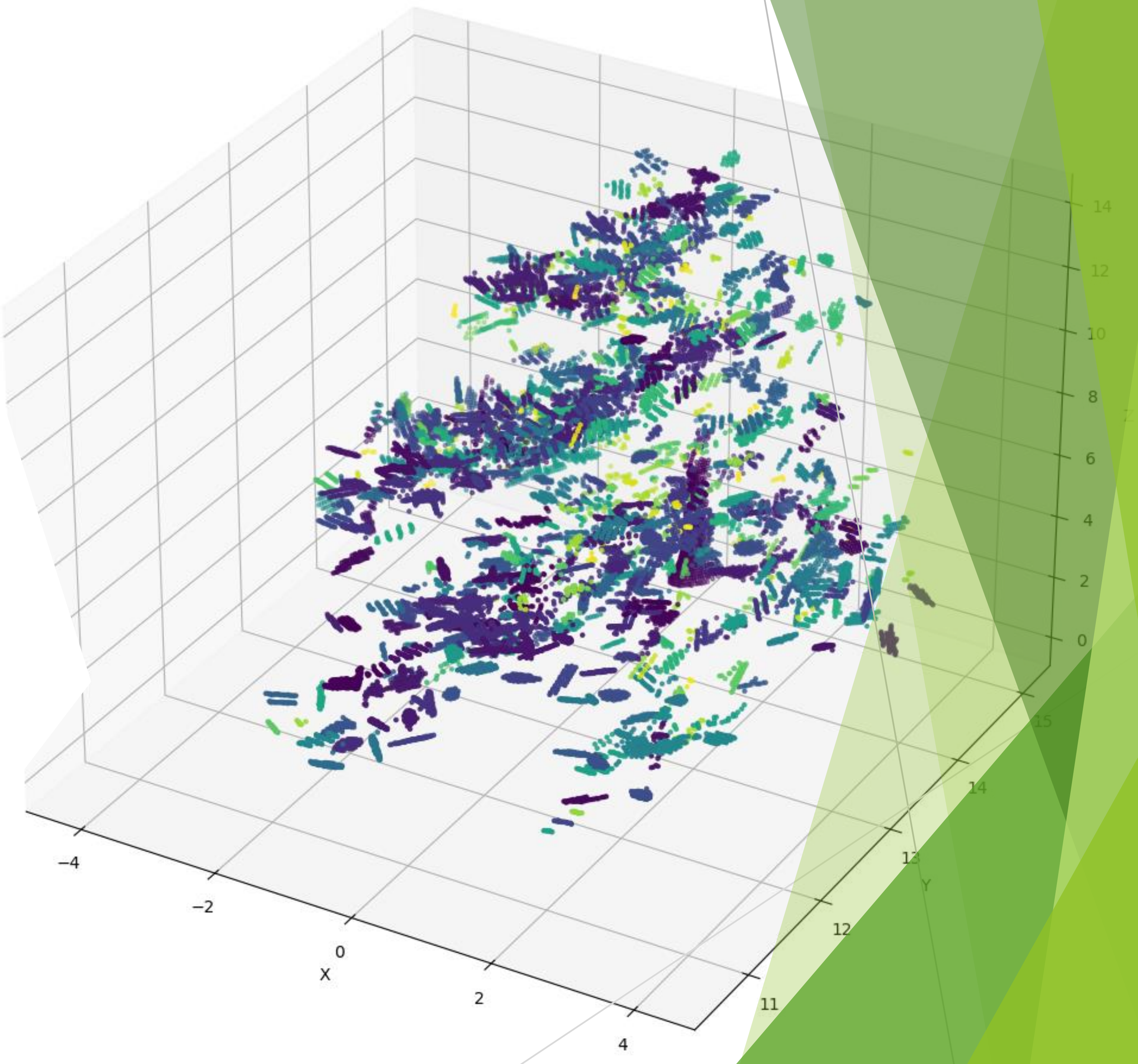
- **RANSAC**: Outlier-proof linear regression



maximize number of points within error tolerant; stochastic

Model – Optimization Initial Clustering

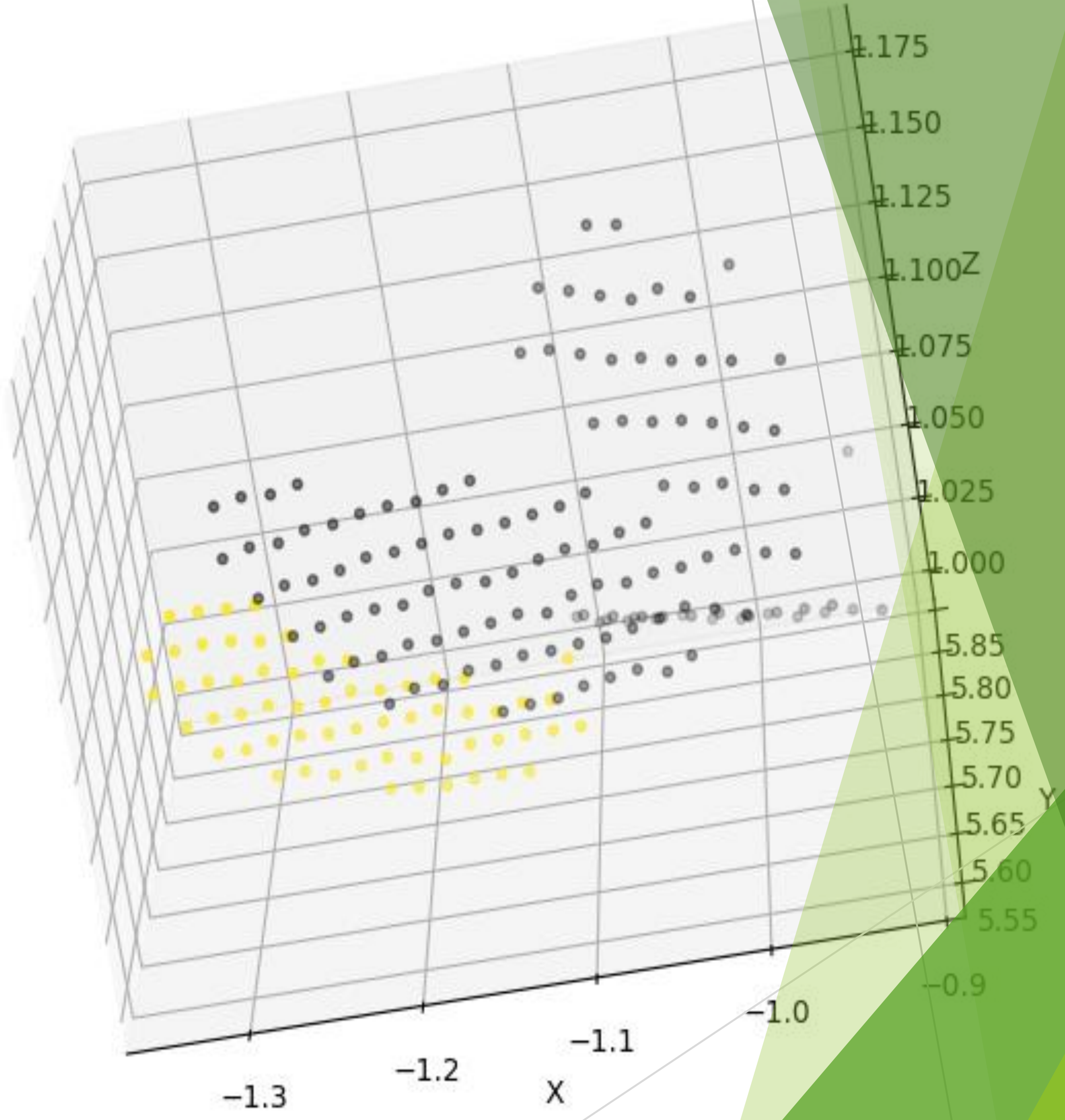
- Cut the whole cloud points into smaller initial clusters.
- These clusters are large enough such that no leaf got fragmented by this step.
- Make it easier and faster for later optimization.
- Use **DBSCAN** with large ϵ and small *minNB*, as it respect the density assumption



Model – Optimization DBSCAN

function DBSCAN_optim(*points*):

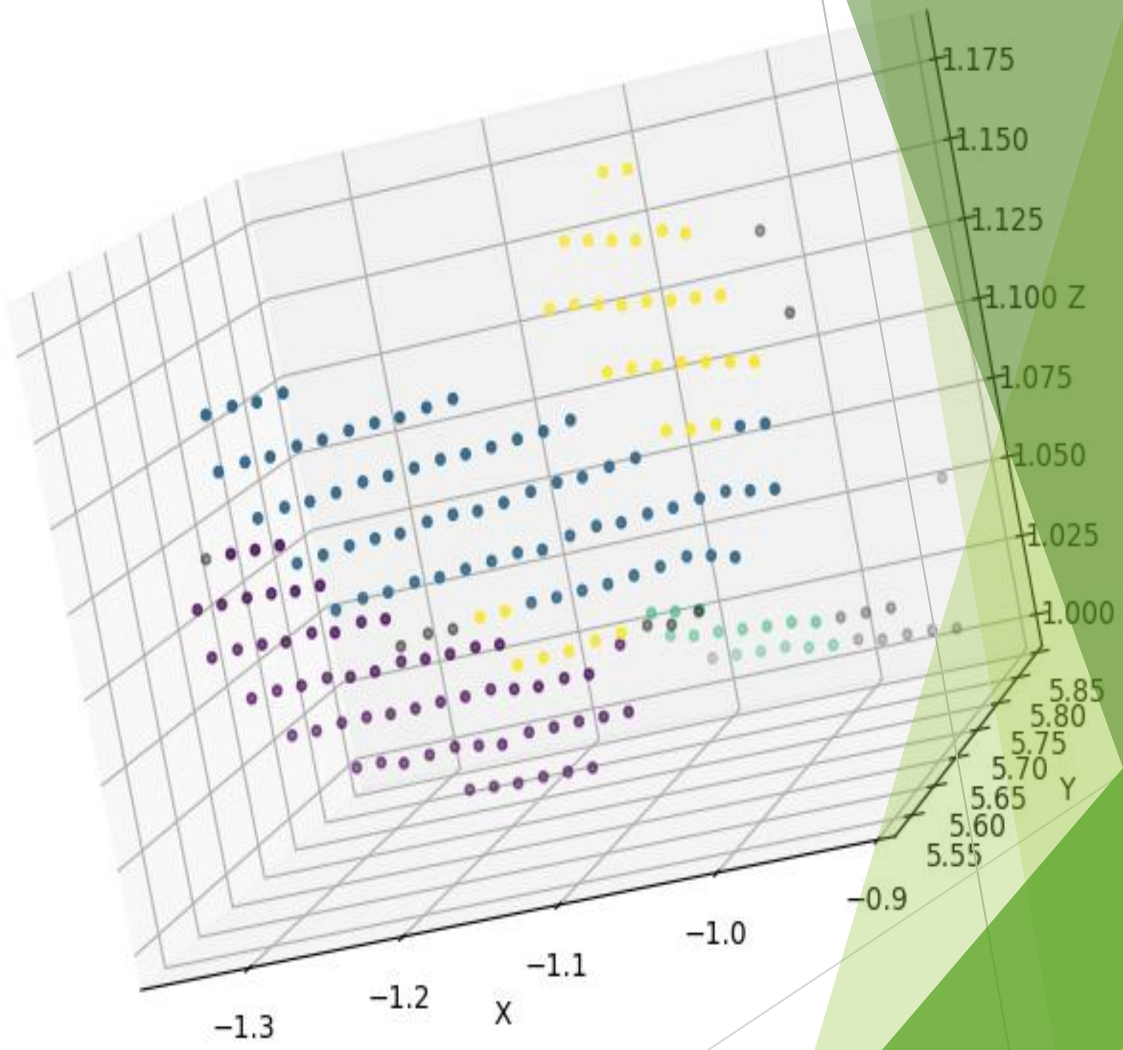
1. chose a pair (ϵ, *minNB*)
2. *clusters* = DBSCAN(*points*, ϵ, *minNB*)
3. for each cluster, remove noise using RANSAC
4. *score* = score_function(*clusters*)
5. return best *clusters* in all pair (ϵ, *minNB*)



Model – Optimization
Sequential RANSAC

function **seq_RANSAC_optim**(points):

1. use **RANSAC** to detect good planar
2. apply **DBSCAN_optim** within the plane to separate different objects on the same plane.
3. collect/remove leaflike clusters from **DBSCAN_optim**
4. repeat leaflike cluster extraction until too few points remain or no new inliers are found.



Strength: separates leaves in dense regions where DBSCAN fail to split.

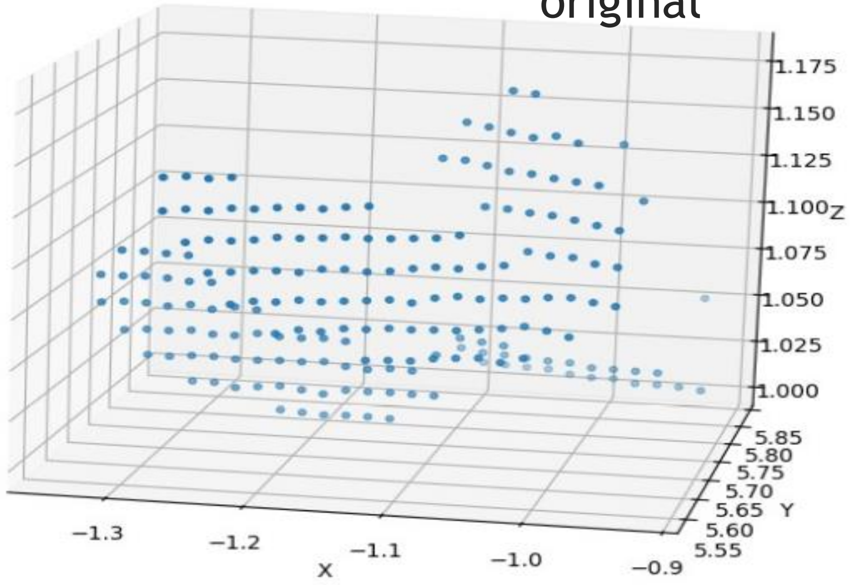
Weakness: planes may cut through objects → risk of over-segmentation; stochastic

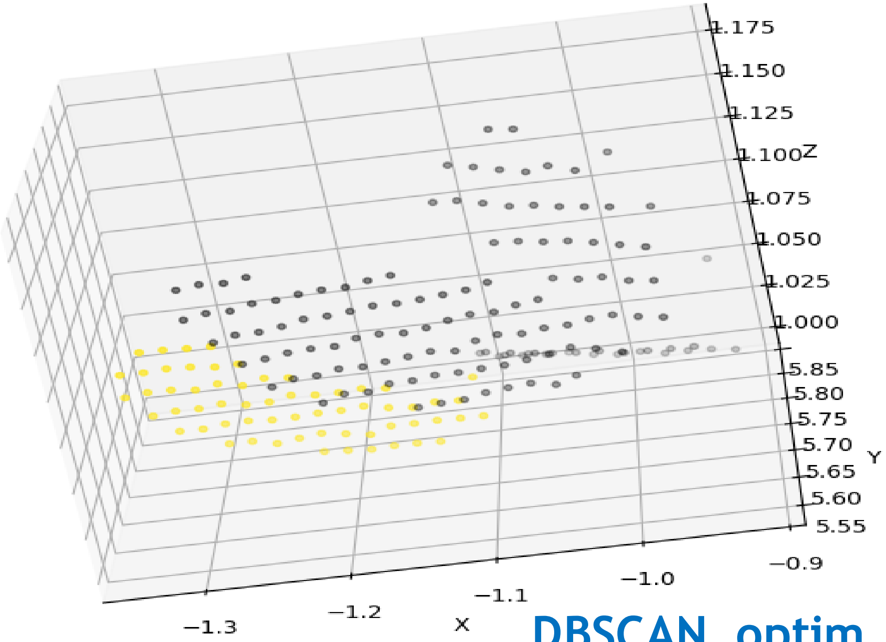
Model – Optimization Final

function **clustering_optim**(*points*)

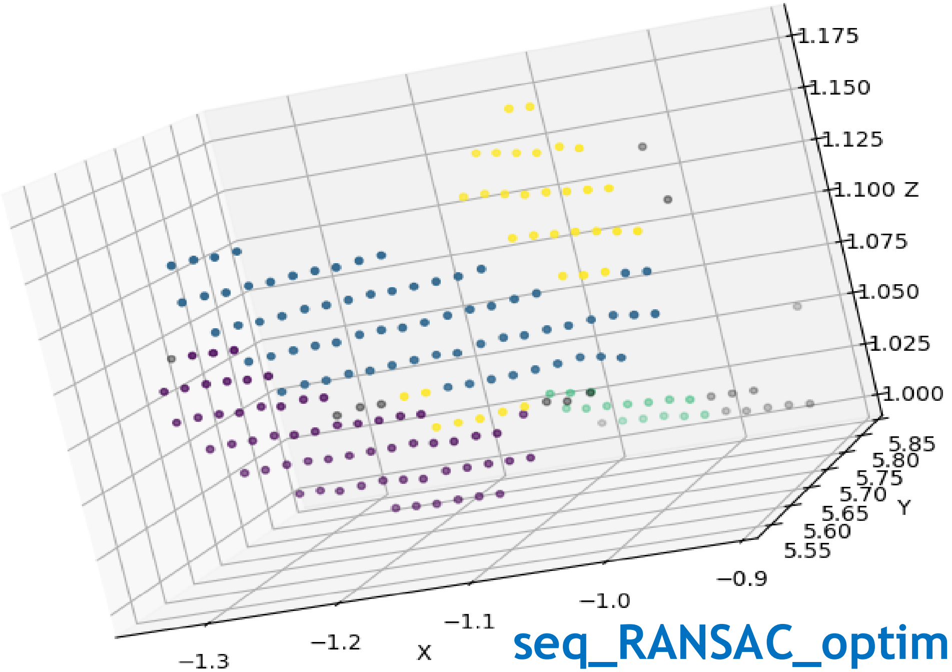
1. *score1*, *clus1* = **DBSCAN_optim**(*points*)
2. *score2*, *clus2* = **seq_RANSAC_optim**(*points*)
3. return the highest score clustering

original





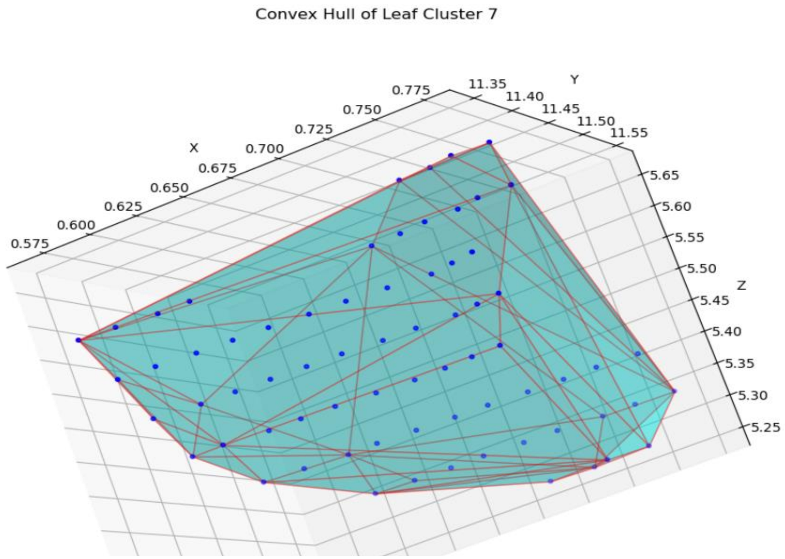
DBSCAN_optim

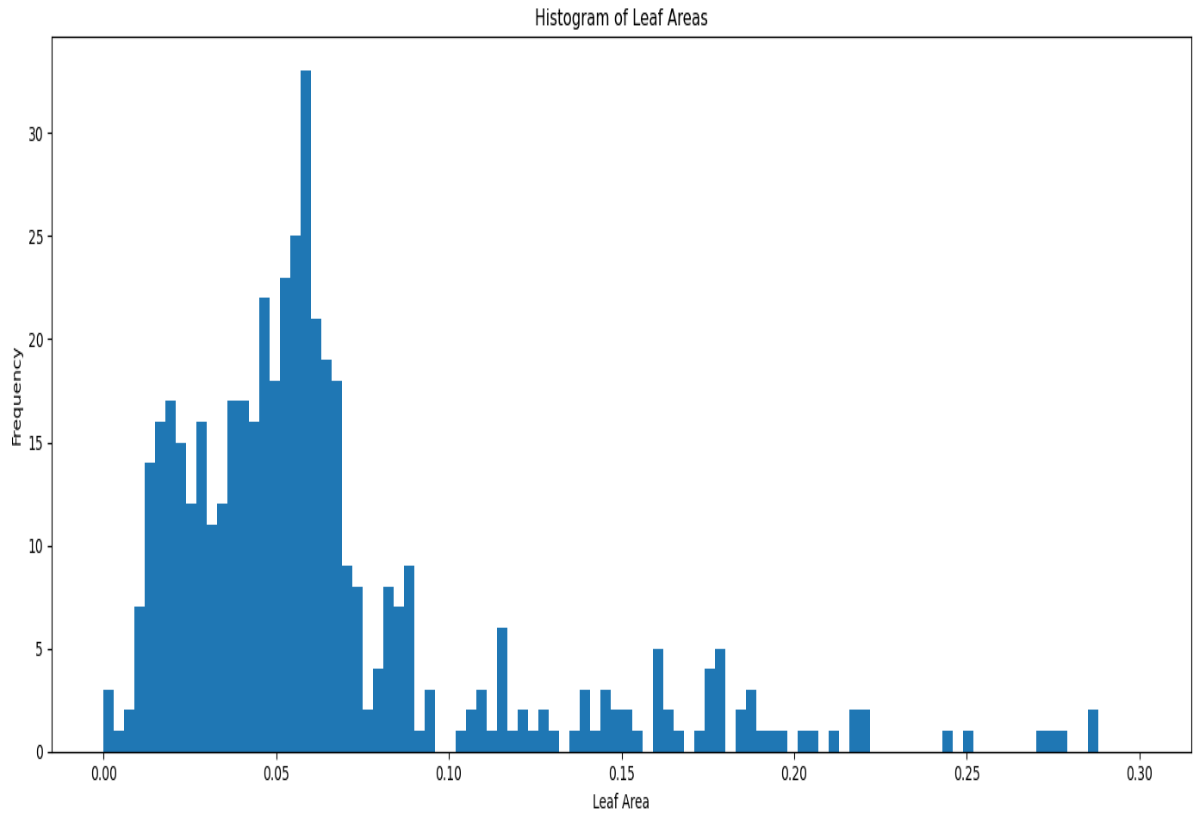


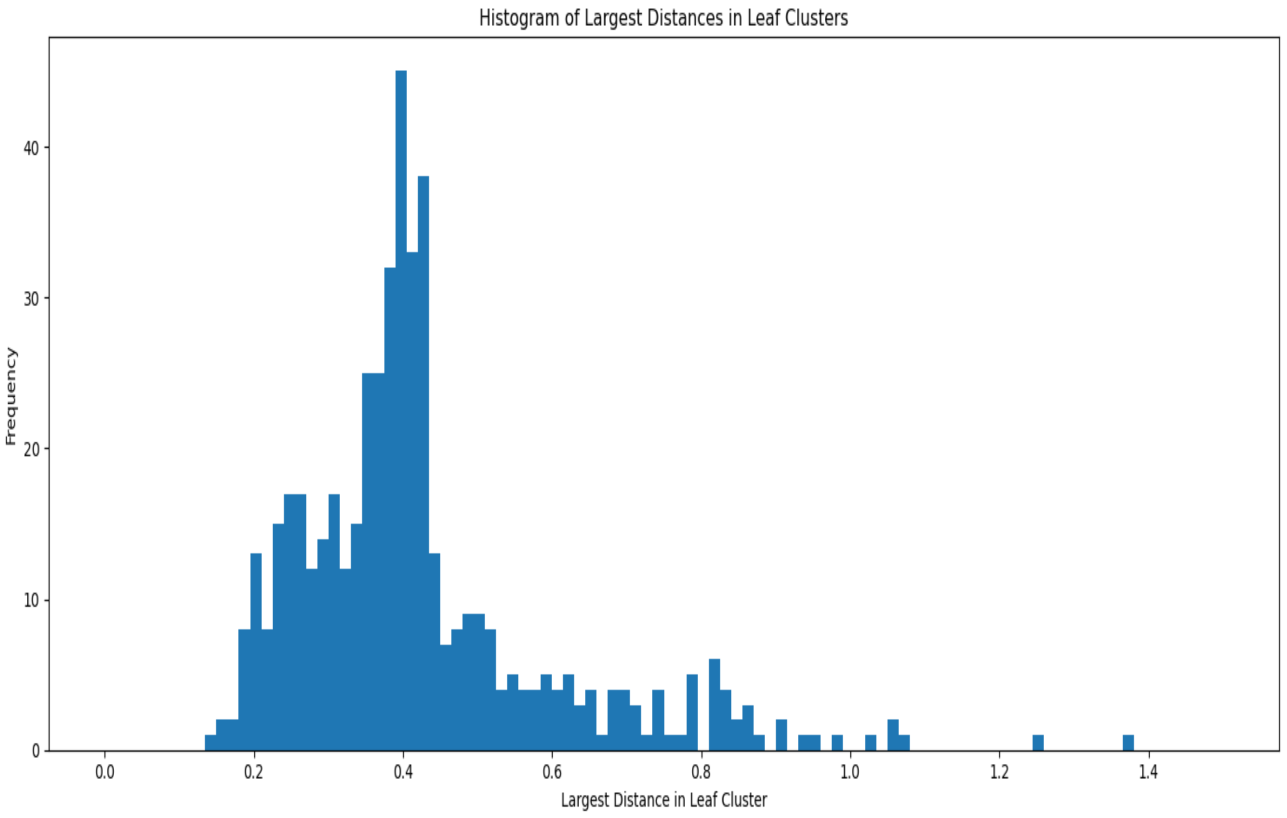
seq_RANSAC_optim

Model – Leaf Size Constrain

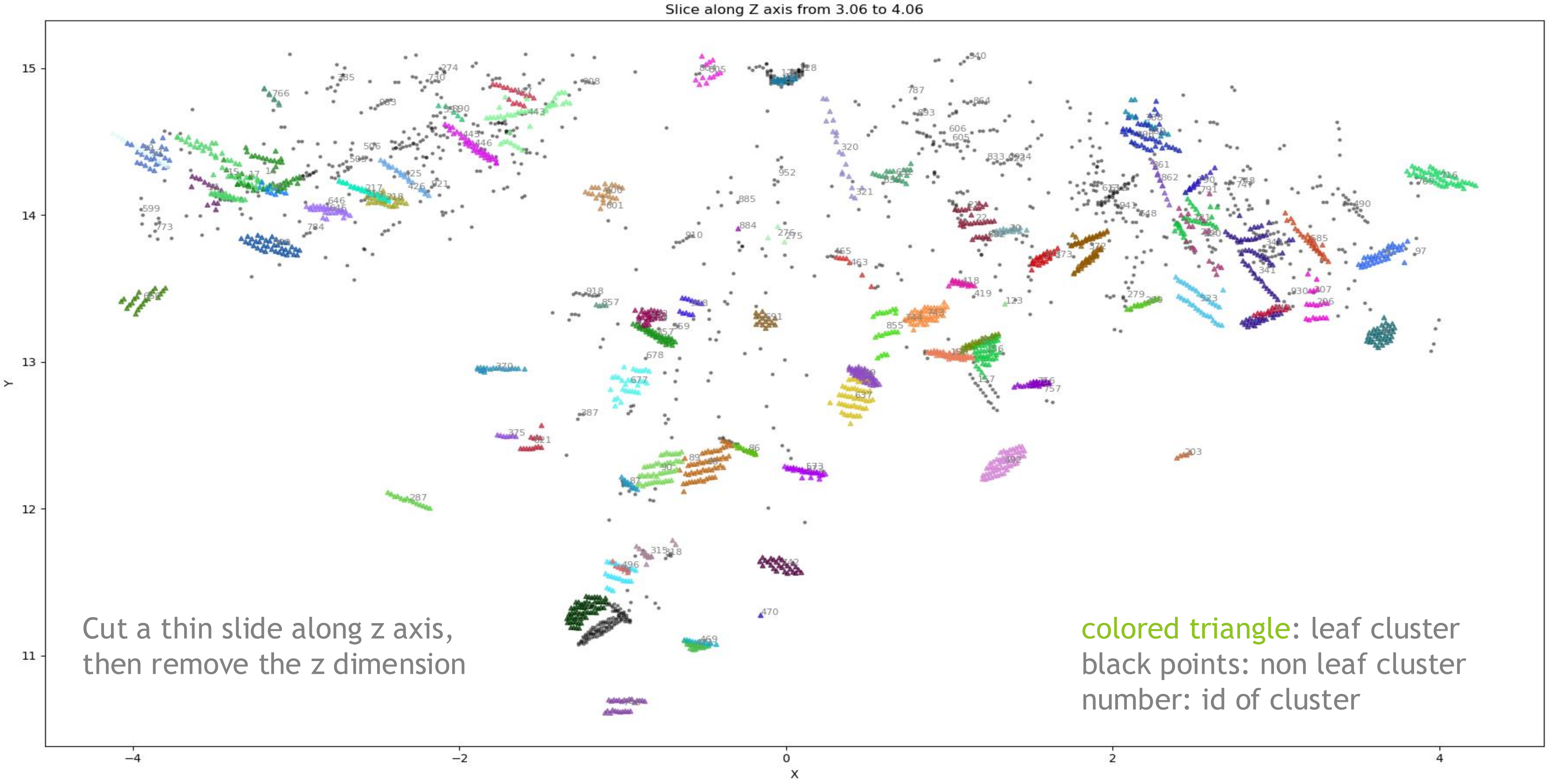
- The size of leaf clusters should be in some reasonable range → constrain by area and, largest distance between 2 points in the clusters.
- *leaf_area* = *0.5* * **surface_area**(**convex_hull**(*cluster*))







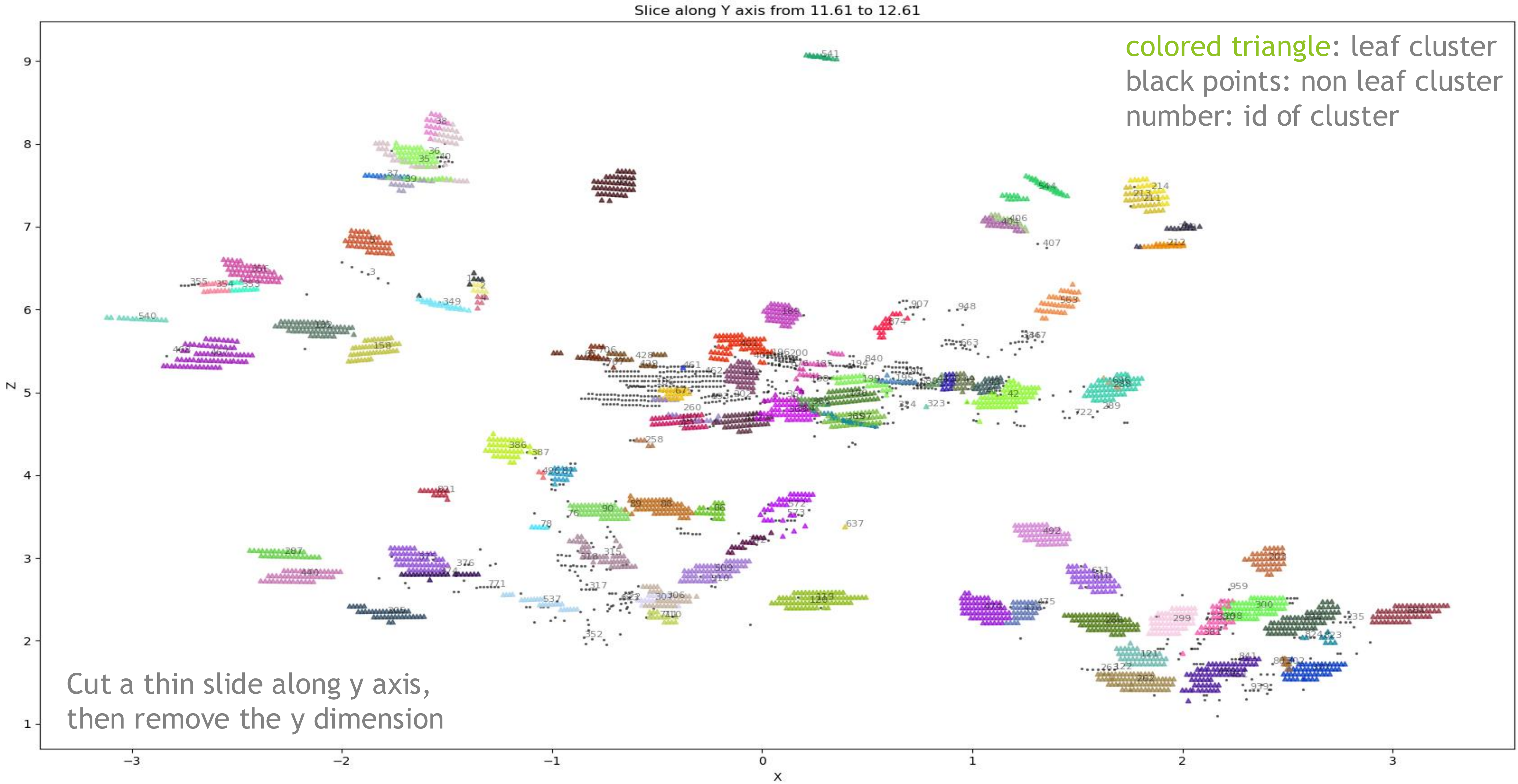
Evaluation – Visual Inspection – CT Scan



Cut a thin slide along z axis,
then remove the z dimension

colored triangle: leaf cluster
black points: non leaf cluster
number: id of cluster

Evaluation – Visual Inspection – CT Scan

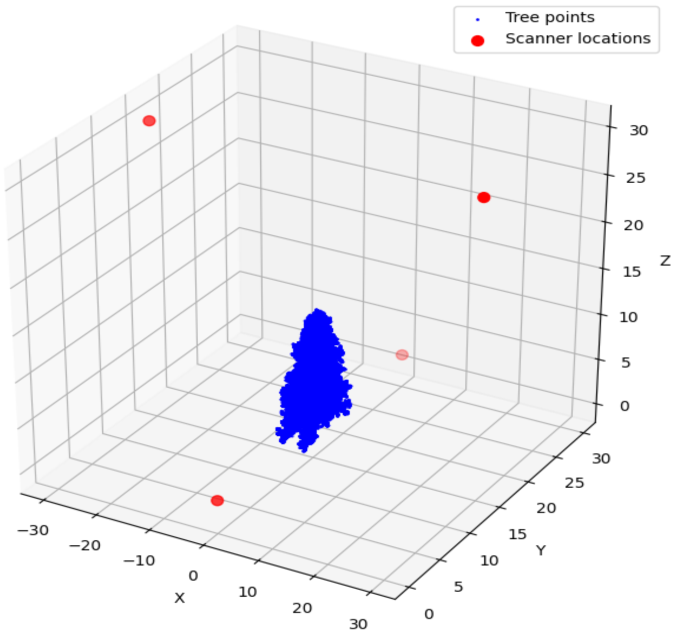


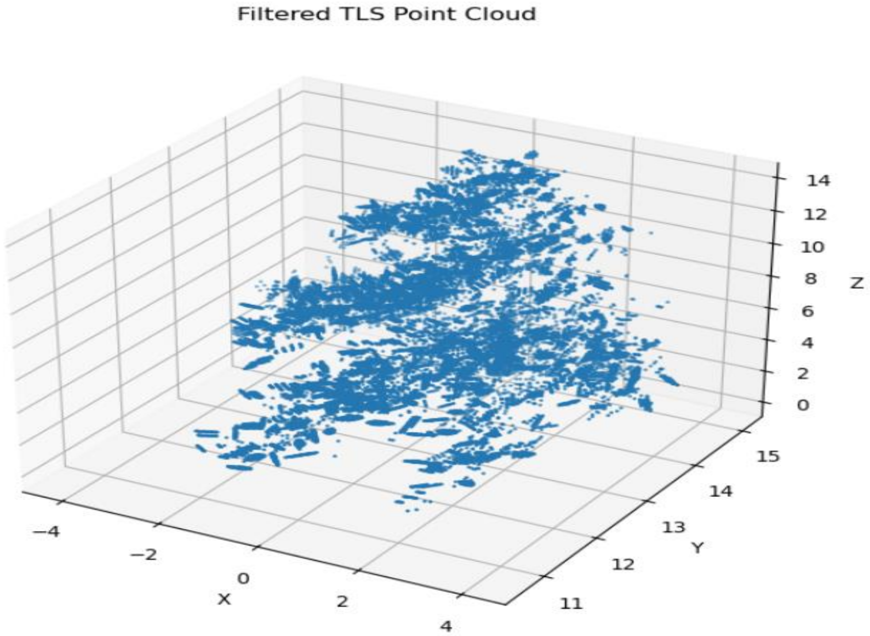
colored triangle: leaf cluster
black points: non leaf cluster
number: id of cluster

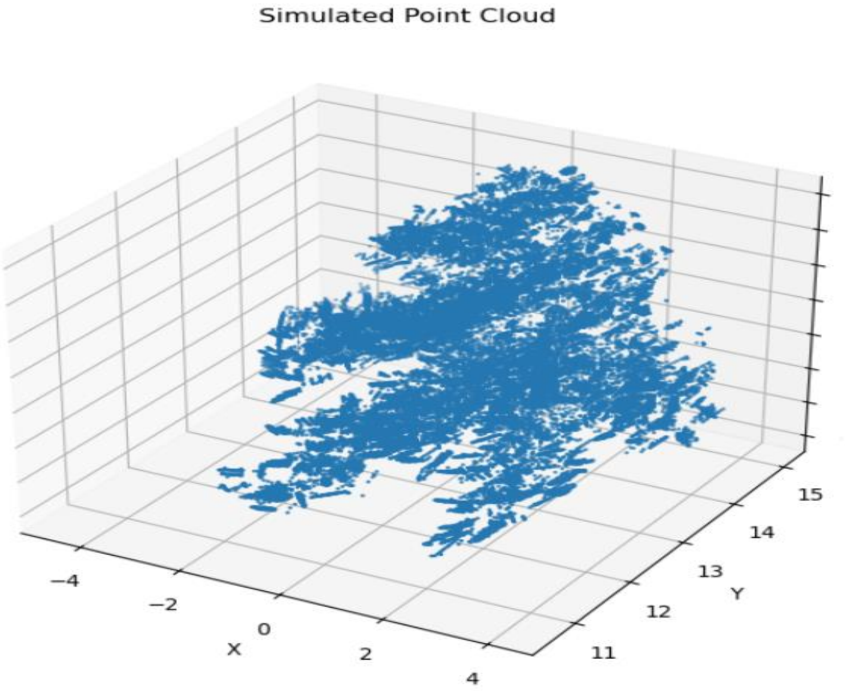
Cut a thin slide along y axis,
then remove the y dimension

Evaluation – Simulated Data

- HELIOS++ was used to create artificial data, but we also found the same tree model as in the assignment
- With 3 added scanners more, previously occluded, leaves were found by using our model







Final Estimation

Estimated on **single-scan** data:

- **916 leaves**
- **55.59 m^2 leaf area**

Estimated on **multi-scan** data:

1256 leaves

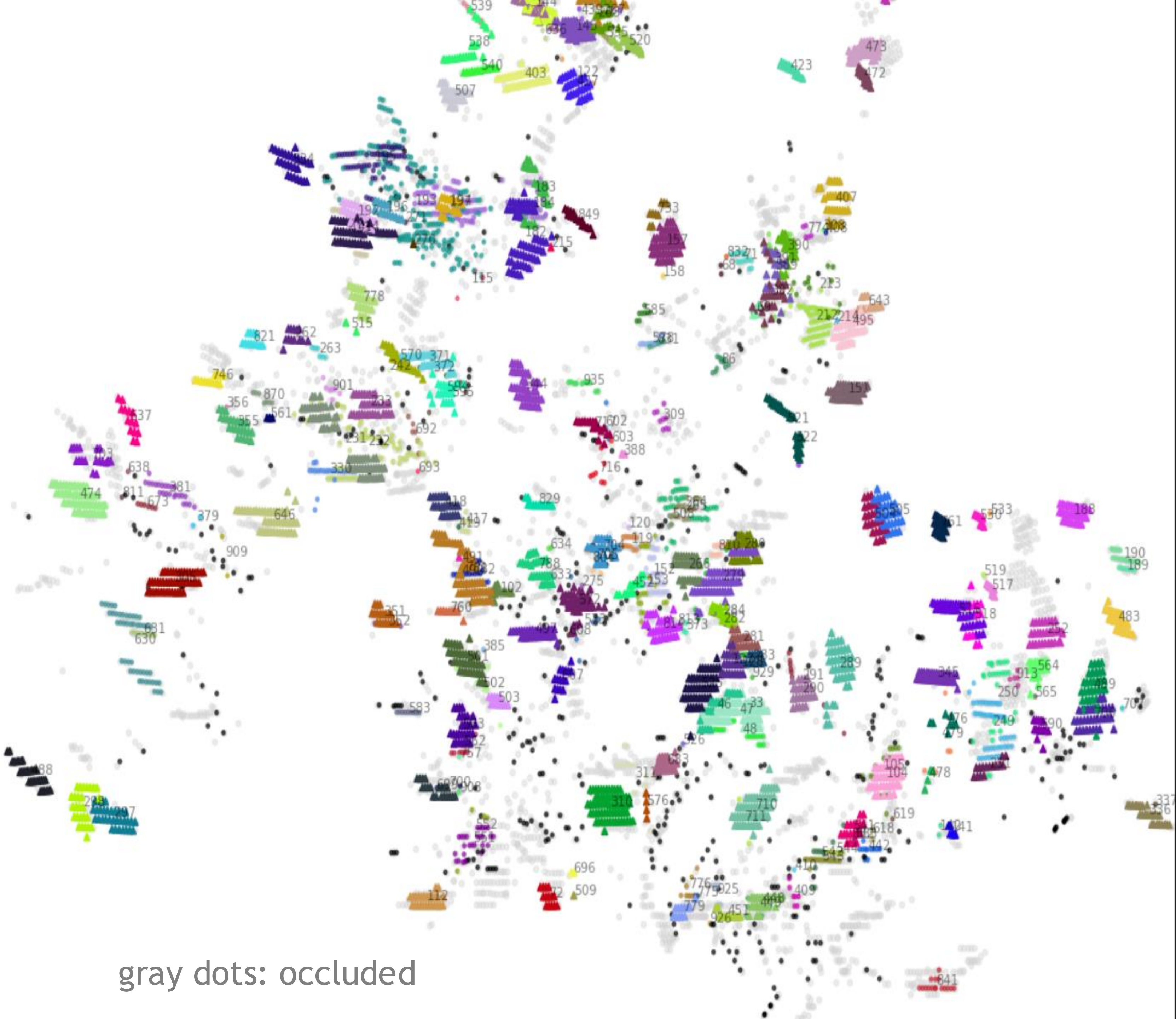
83.52 m^2 leaf area

Underestimation due to occlusion in our single-scan data:

27% for leaf count

33% for leaf area

Maybe even more (~1400-1500 leaves) as **there is still occlusion in multi-scan data**



gray dots: occluded

Conclusion

Limitations:

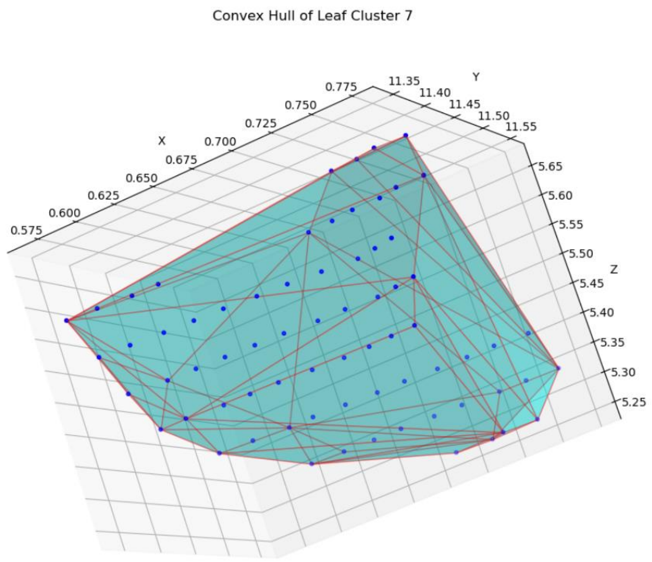
1. Many hand tuned hyperparameters in the method. For new tree species, with different leaf shape, curvature and scan setting, these hyperparameters must be rechecked.
2. Subjective and manual: no labelled data, we relied on qualitative analysis.
3. No clear answer to the occlusion problem. Scanning from multiple angles is very helpful, but there is still occlusion. Some statistical model might be beneficial.

Advantages:

1. No labelled data needed. Which is the case in many real-world situations. Results can be evaluated qualitatively. Although, laborious and prone to error.
2. Explainable. We can clearly understand all the steps, parameters, results in the process.
3. The problem is casted as a constrain optimization problem. Better constrains and clustering algorithm could be added. So, it can be further generalized.

Thank you

Questions?


Convex Hull of Leaf Cluster 7
X
0.575
0.600
0.625
0.650
0.675
0.700
0.725
0.750
0.775
Y
11.35
11.40
11.45
11.50
11.55
Z
5.65
5.60
5.55
5.50
5.45
5.40
5.35
5.30
5.25

Summary

1. Keep only the tree half which faces the scanner.
2. Cluster tree into smaller clusters by **DBSCAN**, reduce the search space of next step.
3. For each smaller cluster, find the best clustering which gives the most leaf-like clusters. **DBSCAN_optim** and **seq_RANSAC_optim** are applied. The leaf-like clusters are identified by shape analysis (**is_leaf_cluster**). Exhaustive search over different parameters and clustering methods, to optimize **score_function**.
4. *Leaf area = haft the* surface area of convex hull of *cluster*
5. Keep leaf clusters which have area and largest dimension in reasonable range.
6. **CT scans** along different axes, for qualitative evaluation.
7. Simulated data from HELIOS++ for estimate the effect of occlusion.