TOWARDS:
INTEGRATING GAUSSIAN SPLATTING WITH
Semantic Labels for Heritage BIM

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Supervisors: Ir. Edward Verbree, Dr. Florent Poux, Msc. Yingwen Yu

OUR GROUP

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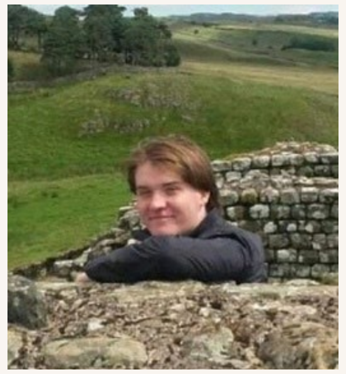

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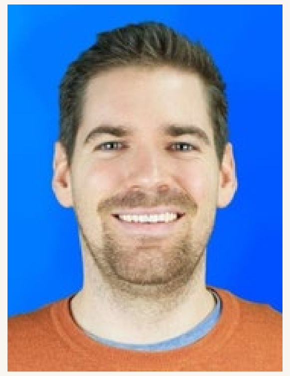
GDMC



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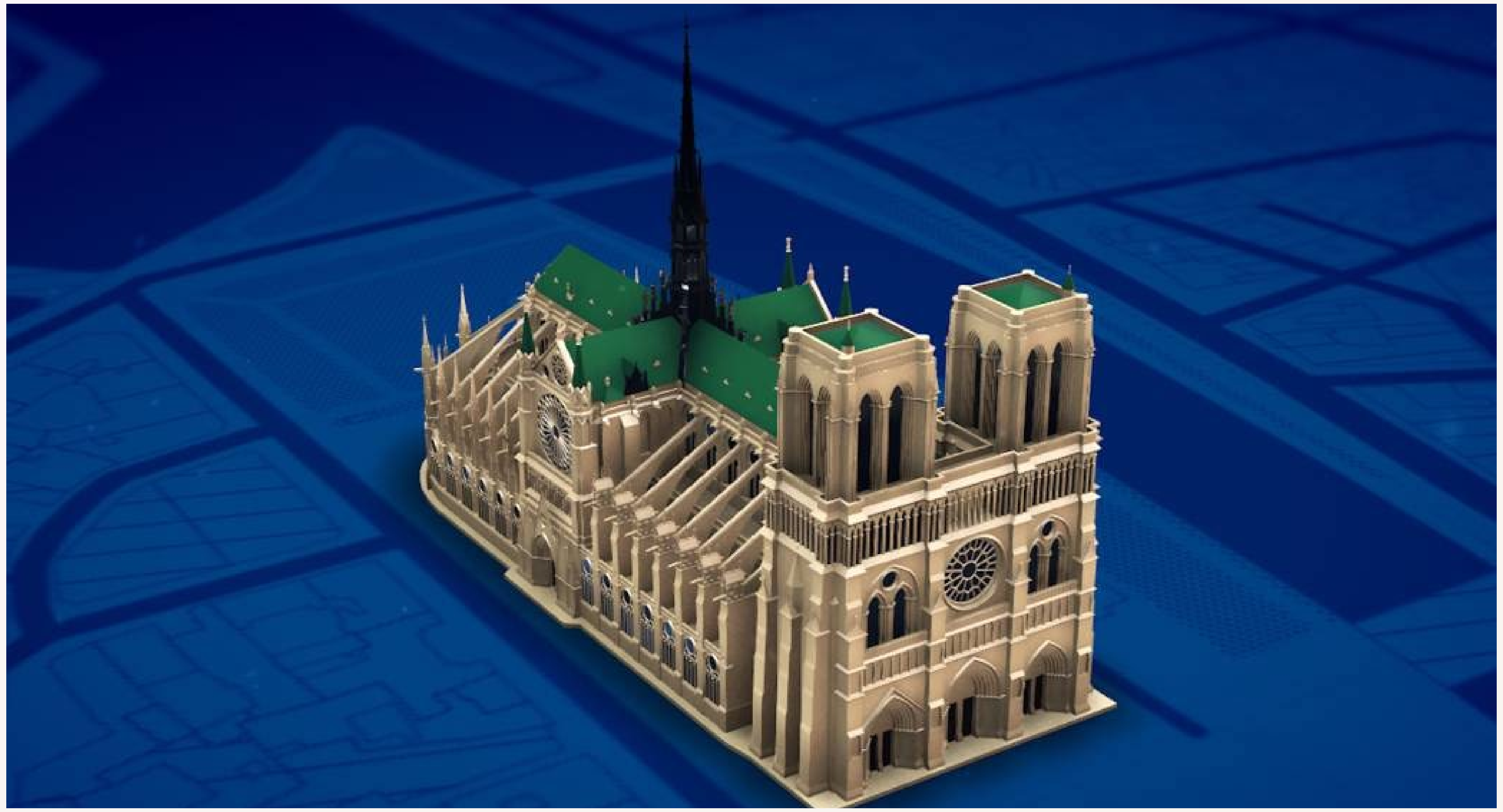
creator of 3D Geodata academy
3D DATA ACADEMY

Ir. Ying Wen ”Christina” Yu
PhD researcher in TUDelft
GDMC

NOTRE DAME

Role of BIM in Notre Dame’s Reconstruction



01

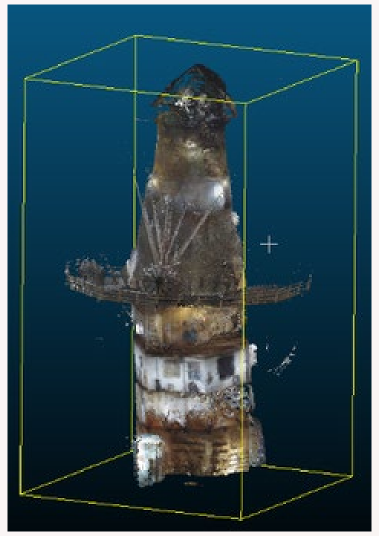
Showing structure

02

Side logistics

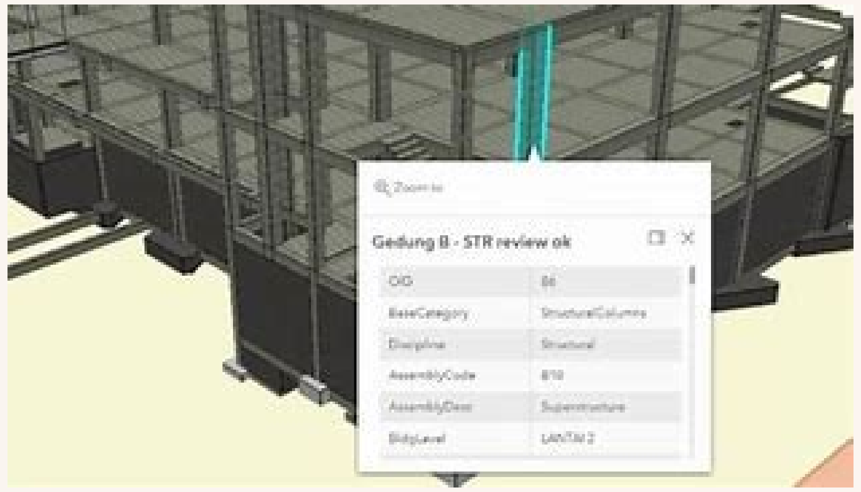
TRADITIONAL H- BIM WORKFLOW

01
Data collection



02
Data
Processing

03
Manually Modelling



04
Information intergration

Current challanges

Time inefficiency
Traditional workflows take a long time, especially when dealing with complex historical buildings

Complex details
Complex decorative details and irregular shapes are difficult to model accurately

Low automation level
Most modeling work needs to be done manually, and the automation level is low

To what extent can a segmented Gaussian splatted point cloud support the heritage Building Information Modeling workflow?

OUR BUILDING

Bouwpub - Delft

OUR RESEARCH PROCESS

Explorative Research

Different scene

- Bouwpub

Trying different input combination

- Panoramic images
- Iphone images
- GeoSlam lidar points

Testing many gaussian splatting implementation

- Inria official
- Postshot
- Polycam
- Lod-3dgs

Applying different segmentation method

- Gaussian Mixture Model
- Segment Aything Model
- K-Means

Data collection

GeoSLAM

Panoramic fish-eye images

Trajectory path

Dense point cloud

iPhone

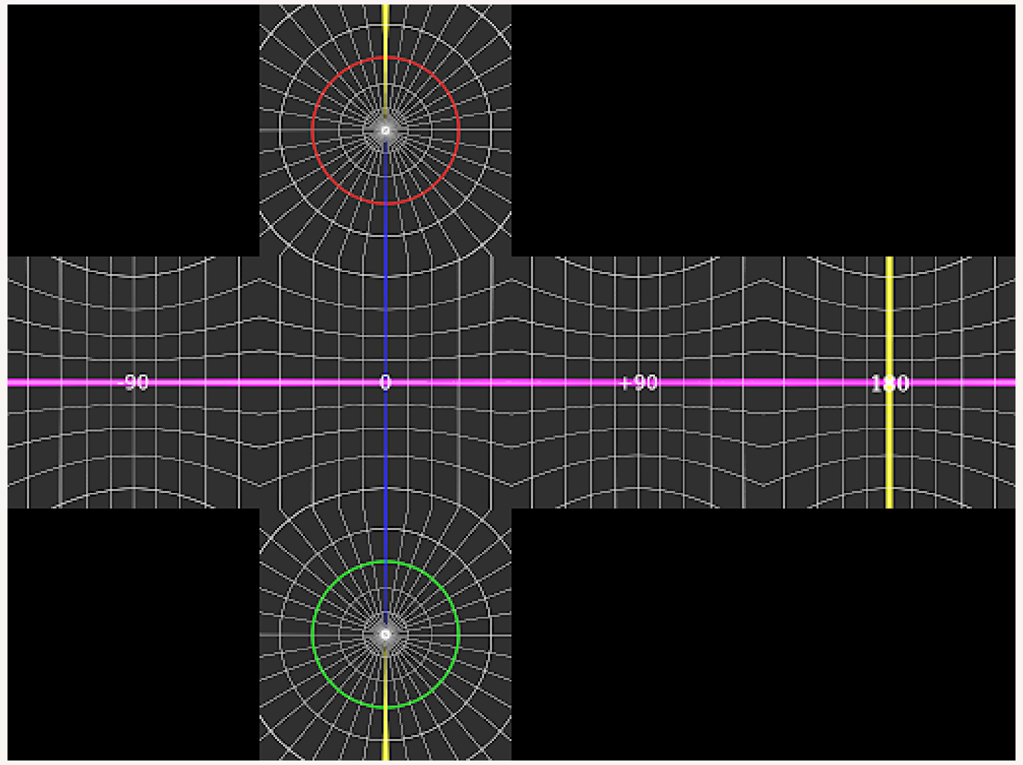
Images

Preprocessing

Cubemapping

Panoramic fish-eye images

Cubemapping

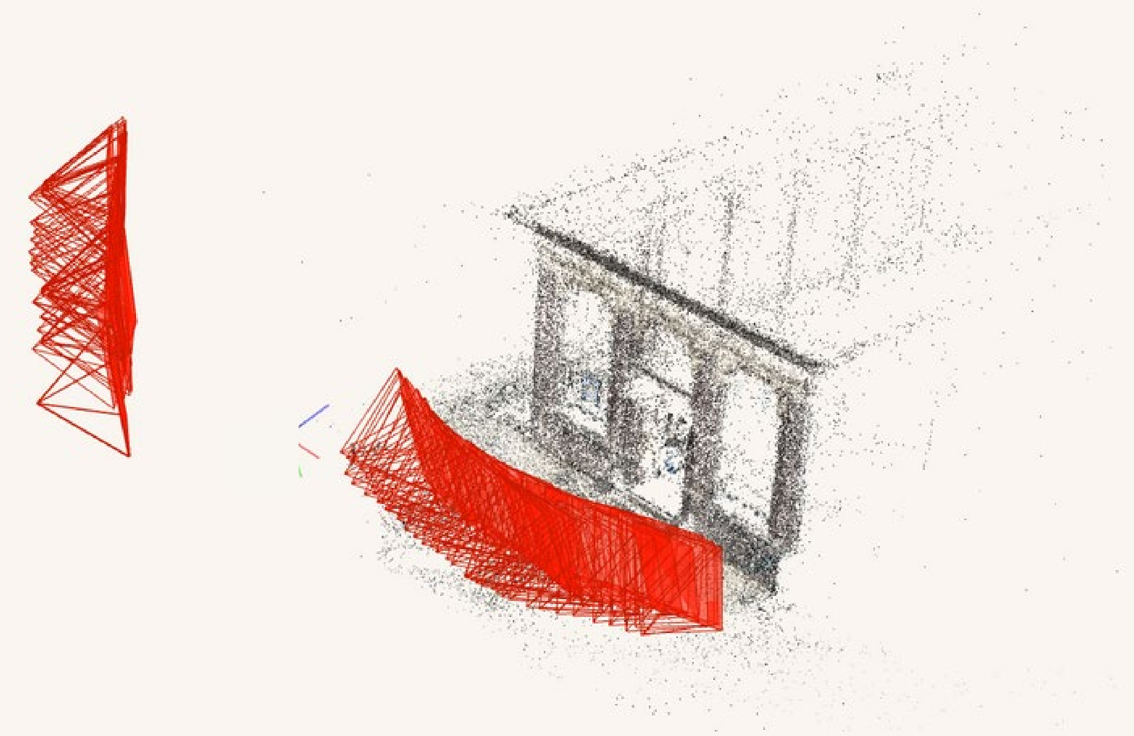


Preprocessing

COLMAP

images

camera pose + sparse point cloud



camera parameters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# Camera list with one line of data per camera:
#   CAMERA_ID, MODEL, WIDTH, HEIGHT, PARAMS[]
# Number of cameras: 395
1 SIMPLE_RADIAL 960 960 479.57929478454162 480 480 0.00041464268471214197
2 SIMPLE_RADIAL 960 960 479.60677535337499 480 480 0.00036969769003919776
393 SIMPLE_RADIAL 960 960 479.11935653923445 480 480    -
0.0010830467088783261
3 SIMPLE_RADIAL 960 960 479.72414359473072 480 480 0.00011827861749425492
.....

# Image list with two lines of data per image:
#   IMAGE_ID, QW, QX, QY, QZ, TX, TY, TZ, CAMERA_ID, NAME
#   POINTS2D[] as (X, Y, POINT3D_ID)
# Number of images: 99, mean observations per image: 7037.3737373737376
1 0.97282531280610474 0.023373424790770599    - 0.22889169357779465
0.025945835664777716 0.43030276360495423      - 1.2473979335306349   -
0.6330897243461634 1 IMG_4278.jpg
1854.0977783203125 2818.621826171875- 1 647.4012451171875 1617.0316162109375
128613 430.837646484375 3380.091552734375     - 1 1774.3994140625
2092.046142578125  - 1 735.22174072265625 2818.510009765625   - 1 1871.365478515625
3102.653564453125  - 1 1235.427001953125 1698.631103515625 126320
2134.7666015625 3521.619384765625   - 1
.....
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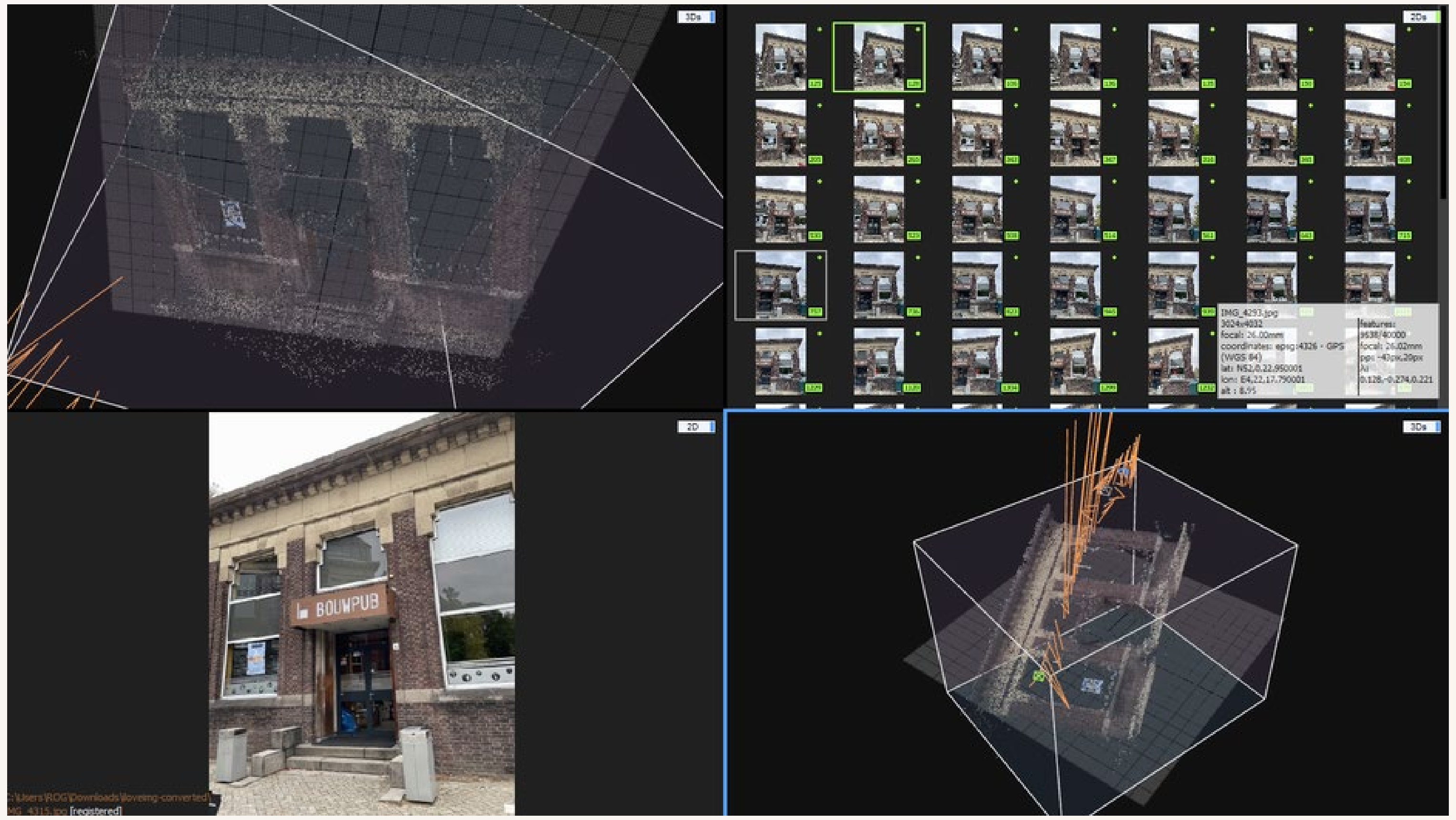
Preprocessing

RealityCapture

images

camera pose + sparse point cloud

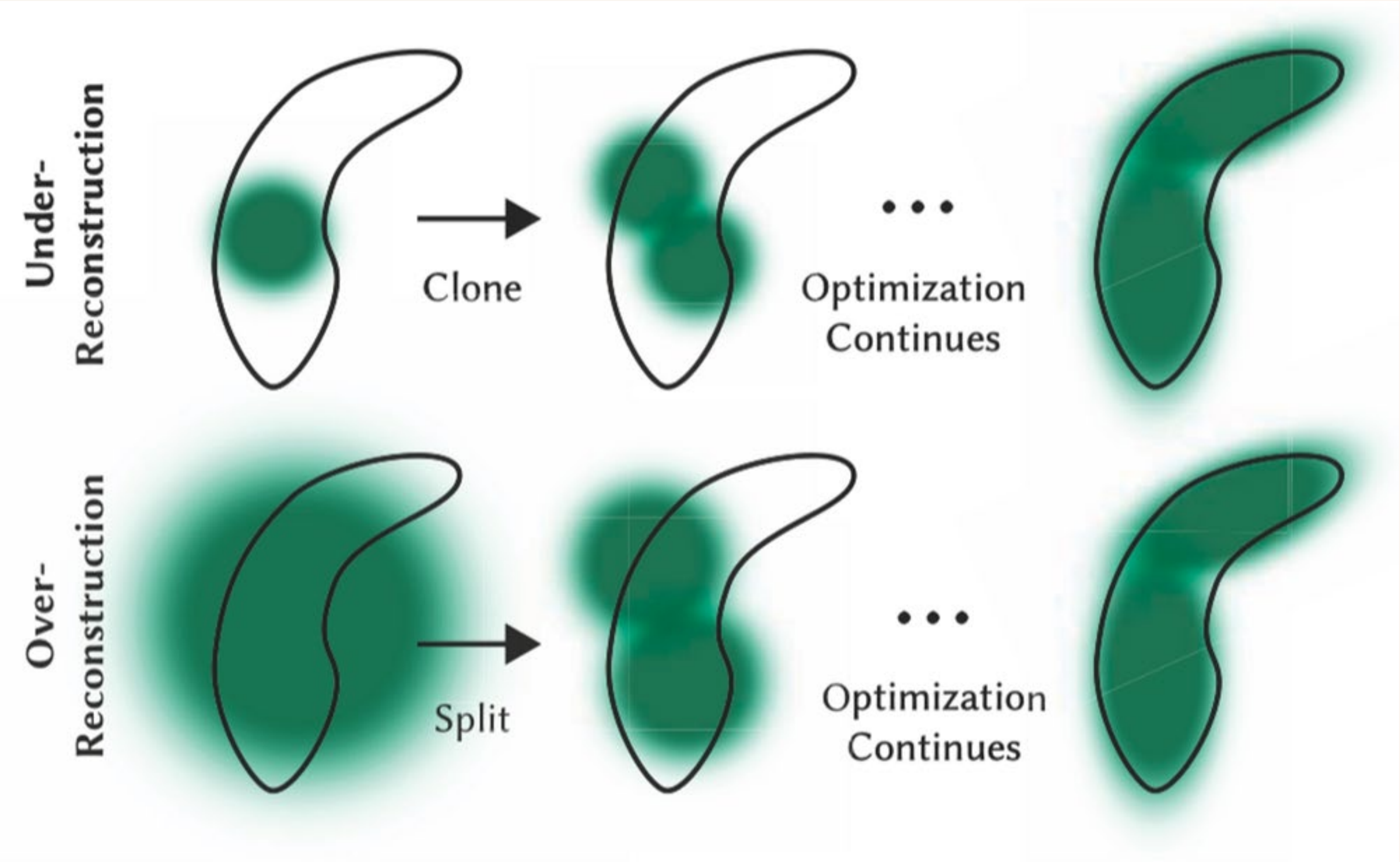


Advantages vs COLMAP

- More optimized processing speed
- User-friendly interface with streamlined workflow
- Better handling of large datasets
- Direct CSV export for camera poses

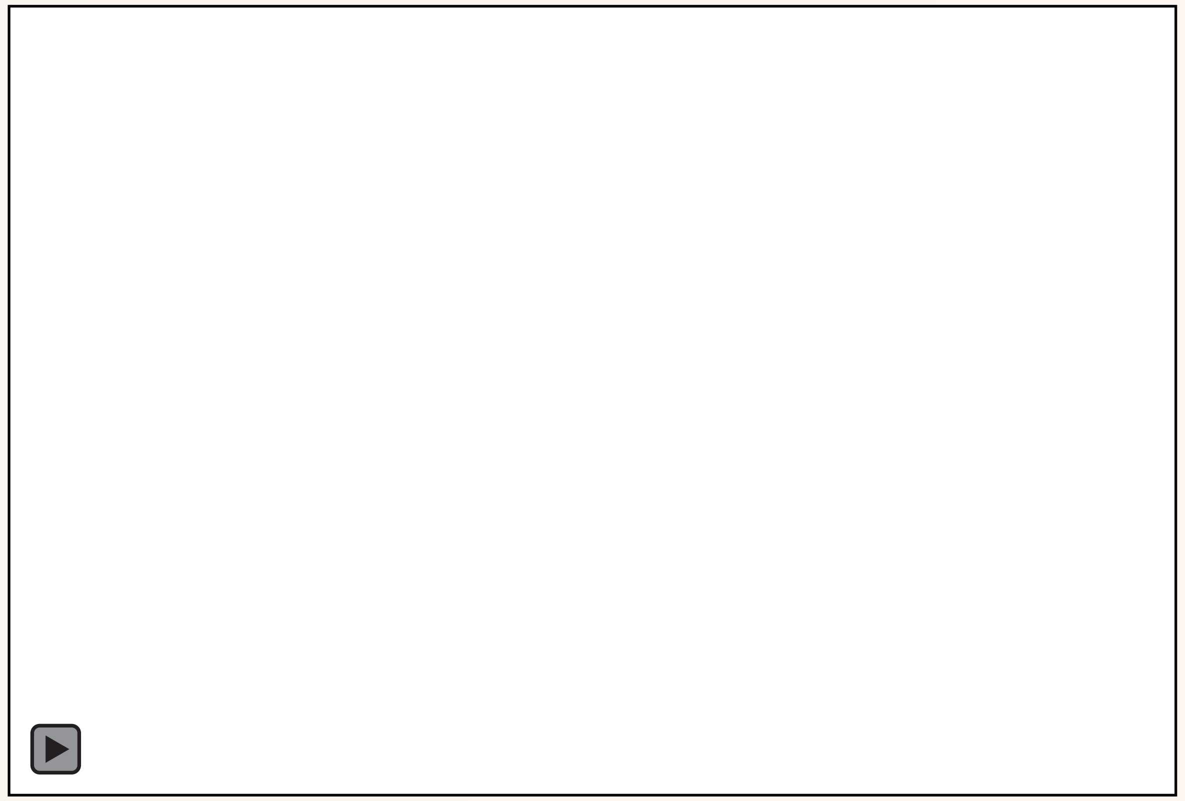
How Gaussian splatting works

- Gaussian splatting process
- Take a sparse point cloud
- Image’s and their position
- Iteratively define a Gaussian for each point to create a global best fit through training



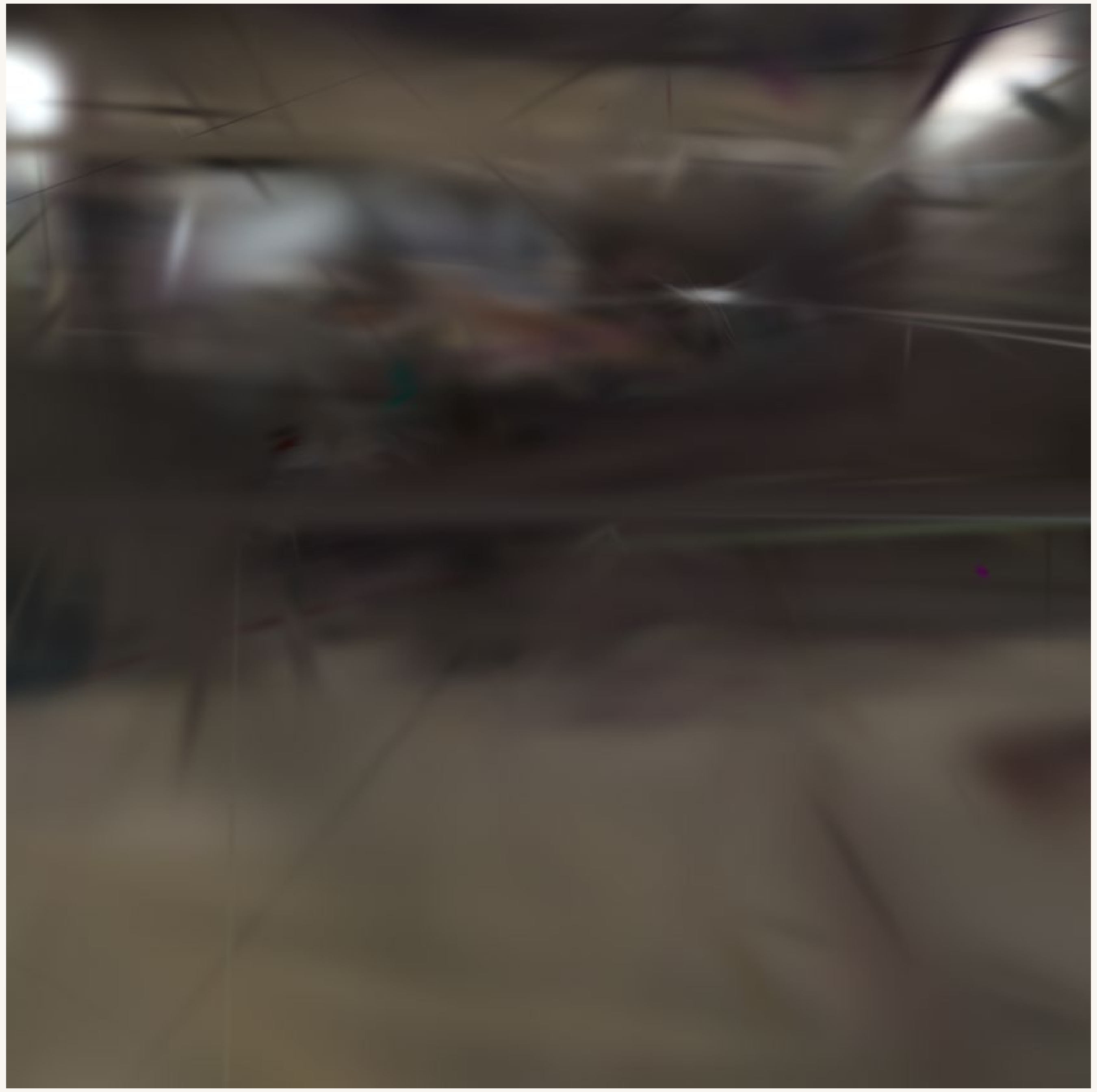
A Gaussian consists of

- Position
- Covariance matrix
- Color (spherical harmonics)
- Opacity



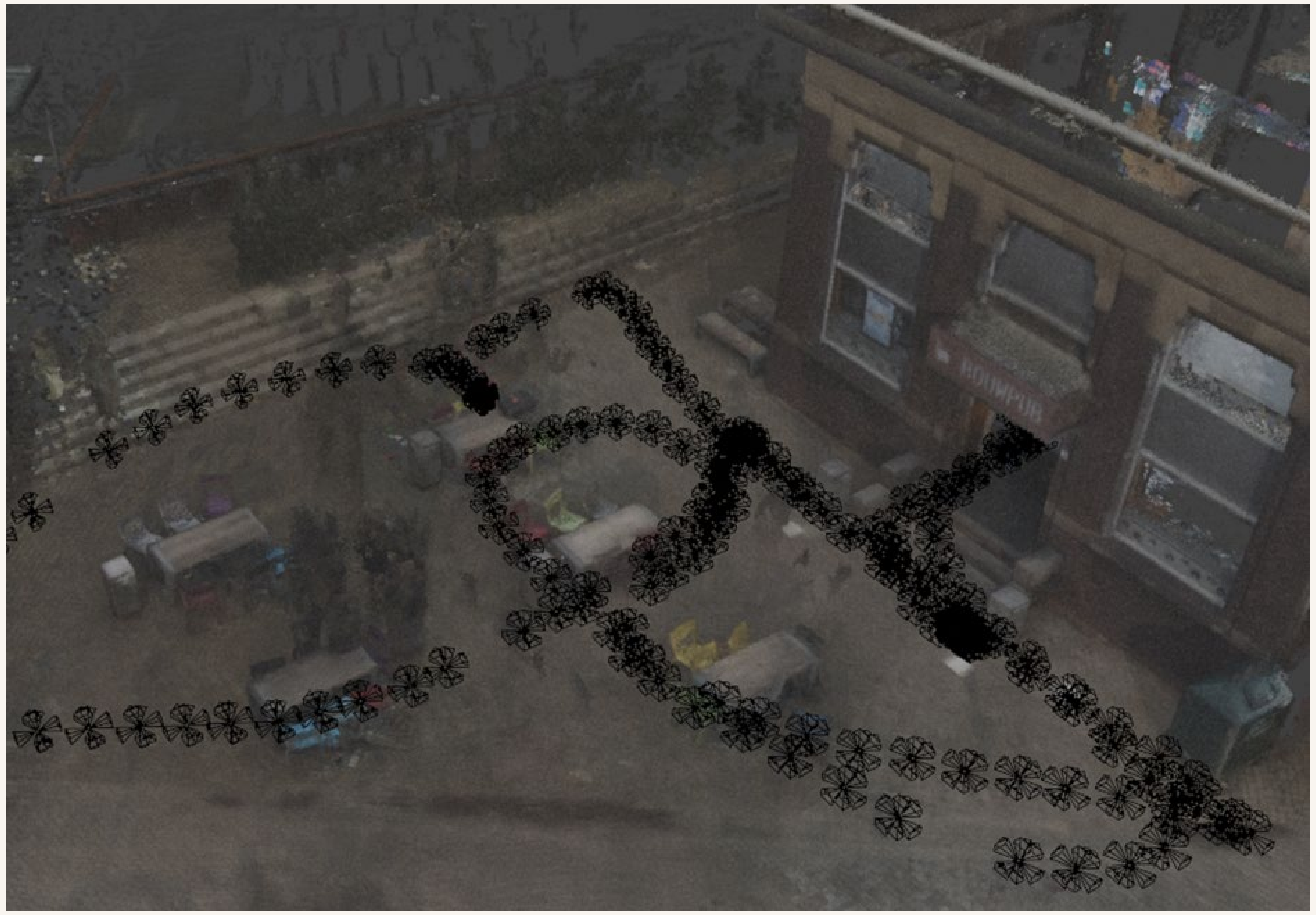
Gaussian Splatting software

LetsGo: Large-Scale Garage Modeling and Rendering via LiDAR-Assisted Gaussian Primitives	Inria	Blender
Photo's + Pointcloud	Photo's	Photo's + Pointcloud
LOD 3DGS	Inria Polycam Postshot	Edwardian Splatting



LOD 3DGS

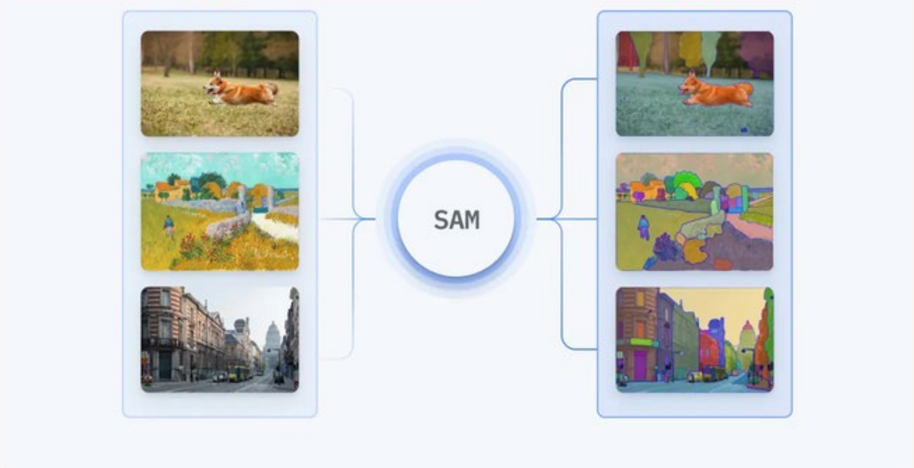
INRIA, POLYCAM AND POSTSHOT

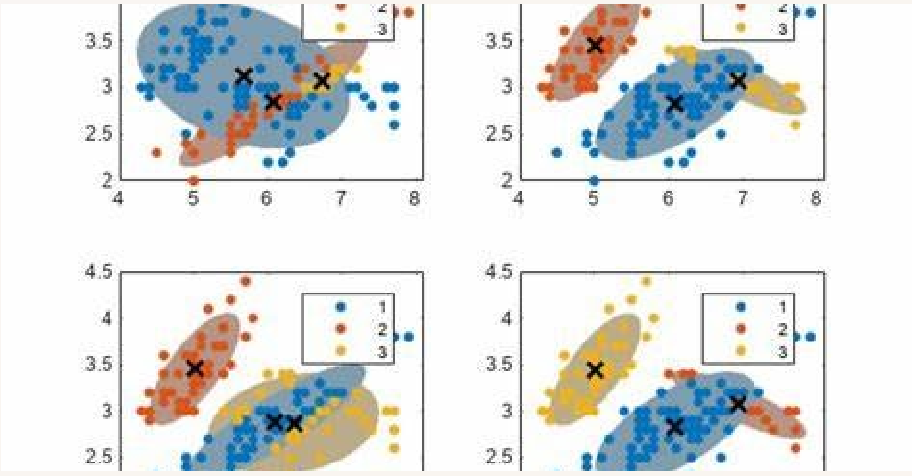


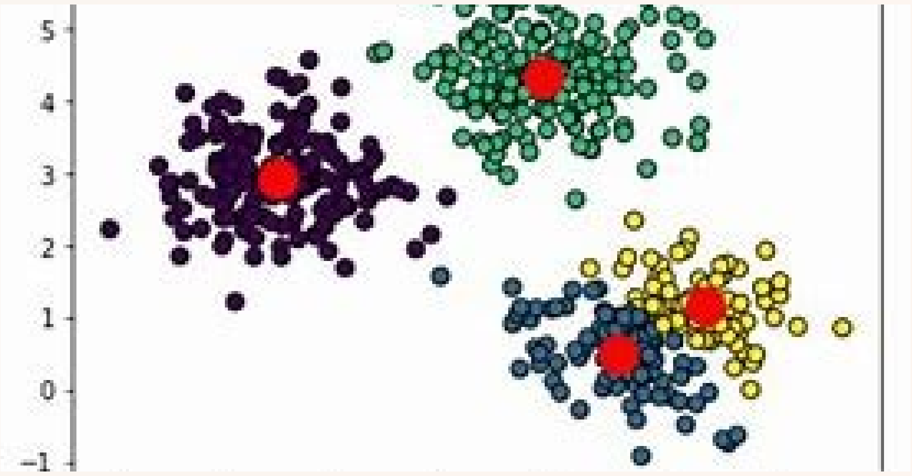
EDWARDIAN SPLATTING

Segmentation

Segmentation Models







Segment Anything Model

A pretrained, deep-learning model that segments objects in images based on user prompts, adaptable across varied datasets.

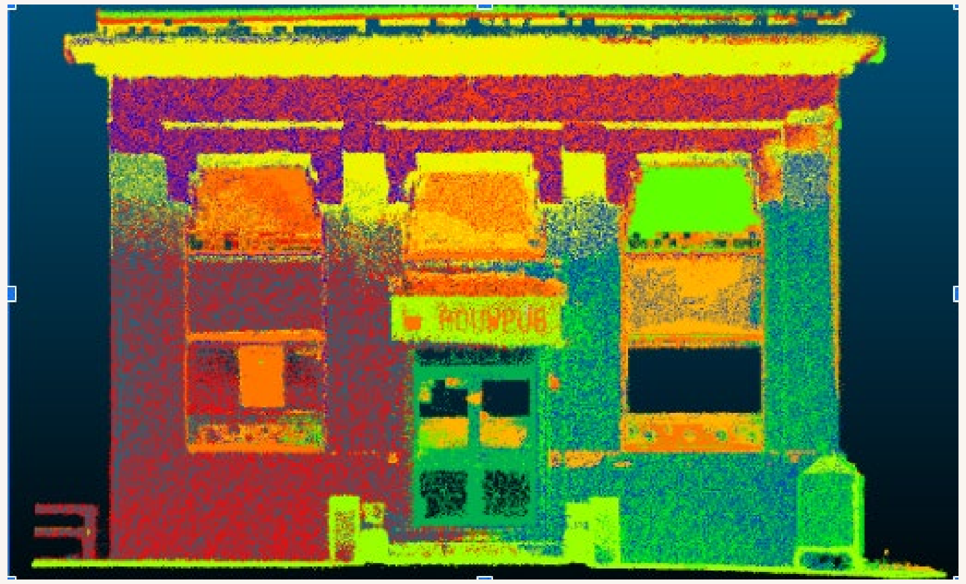
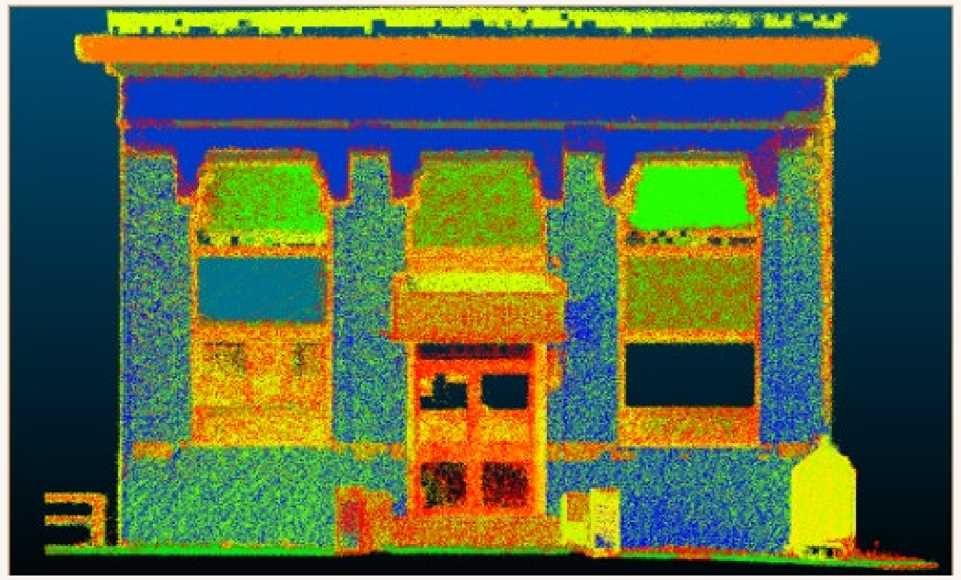
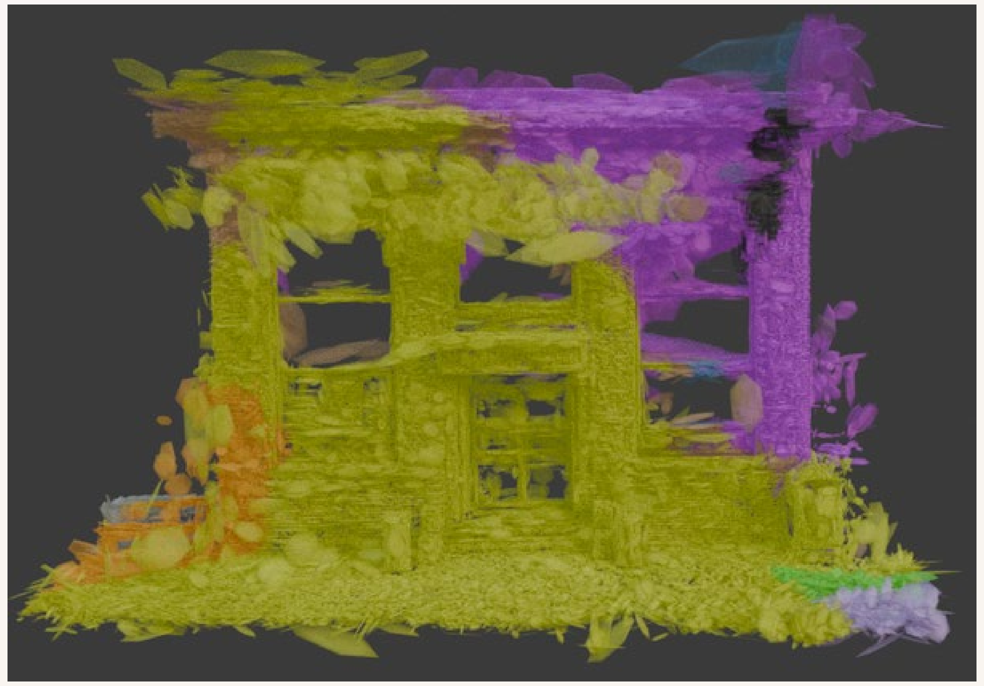
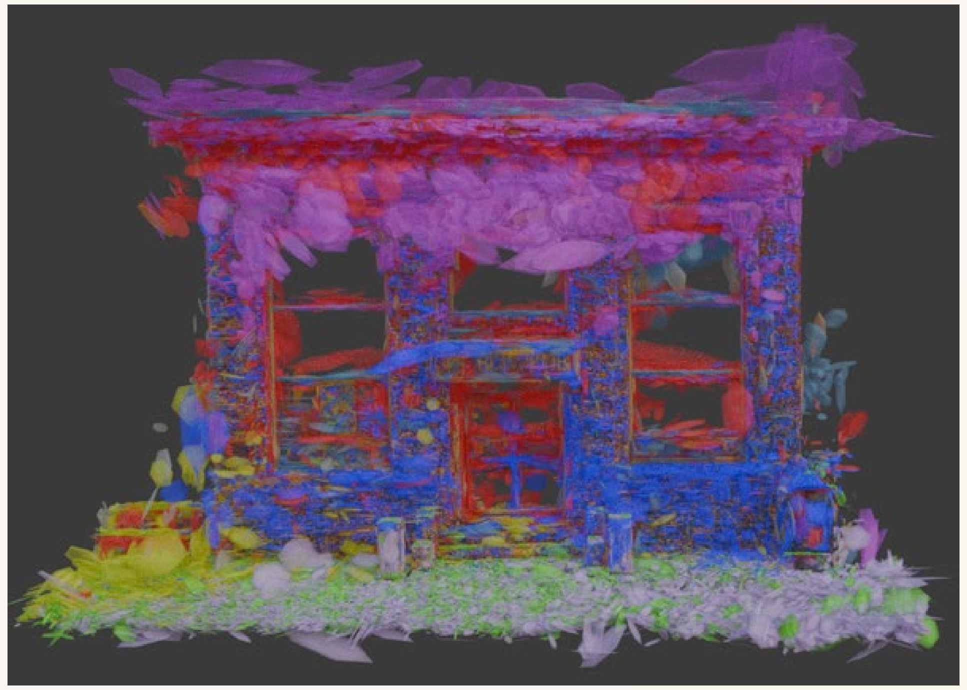
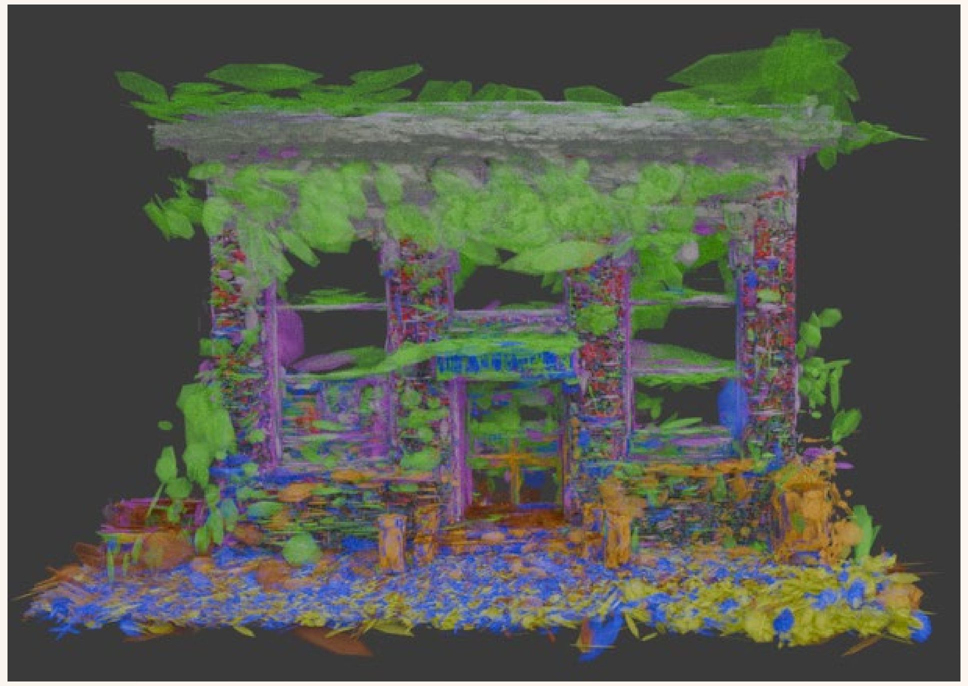
Gaussian mixture

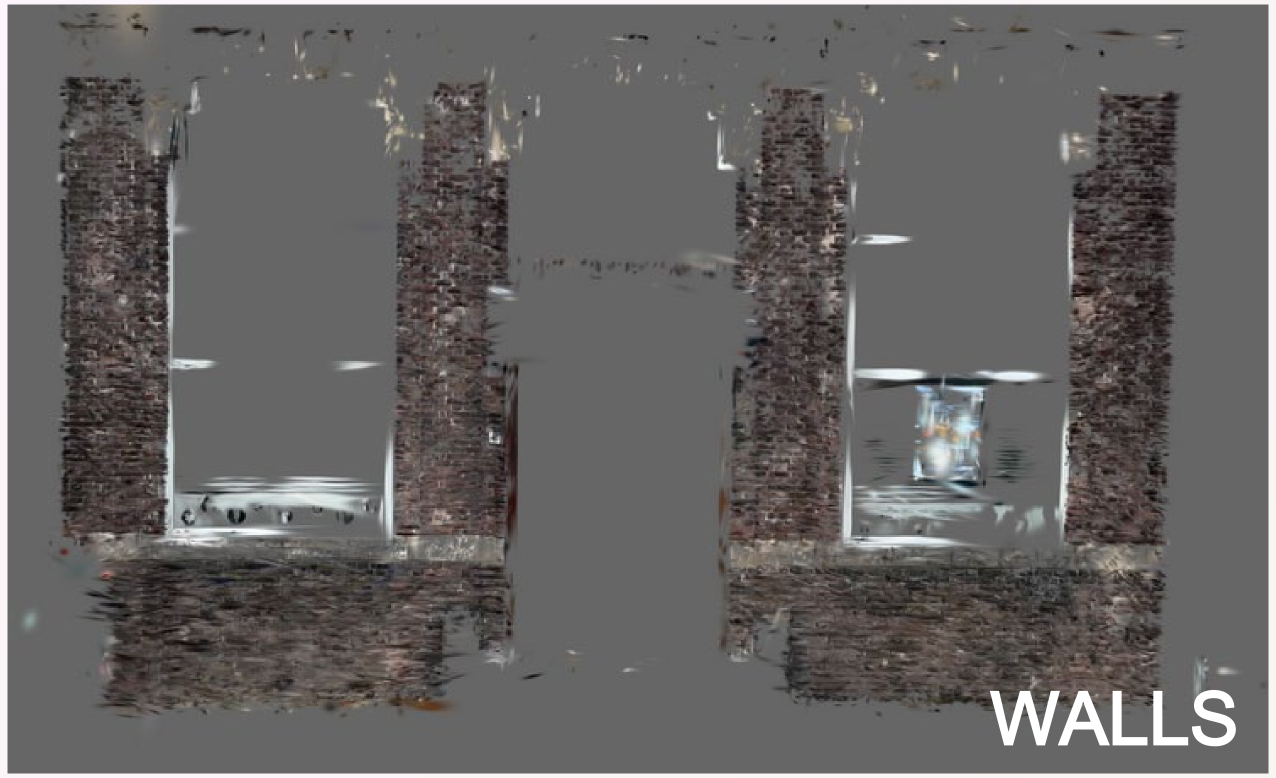
A probabilistic model that assumes data is generated from multiple Gaussian distributions, useful for complex, overlapping segmentations.

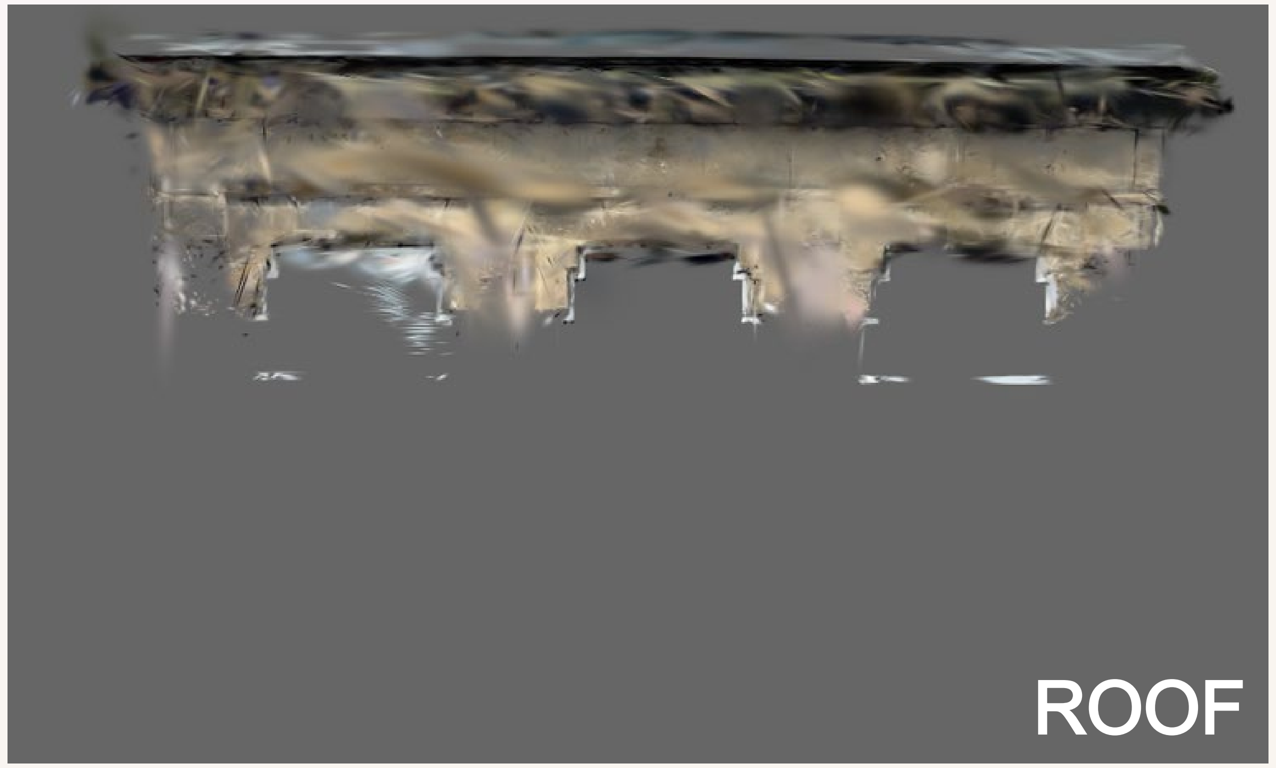
K- means

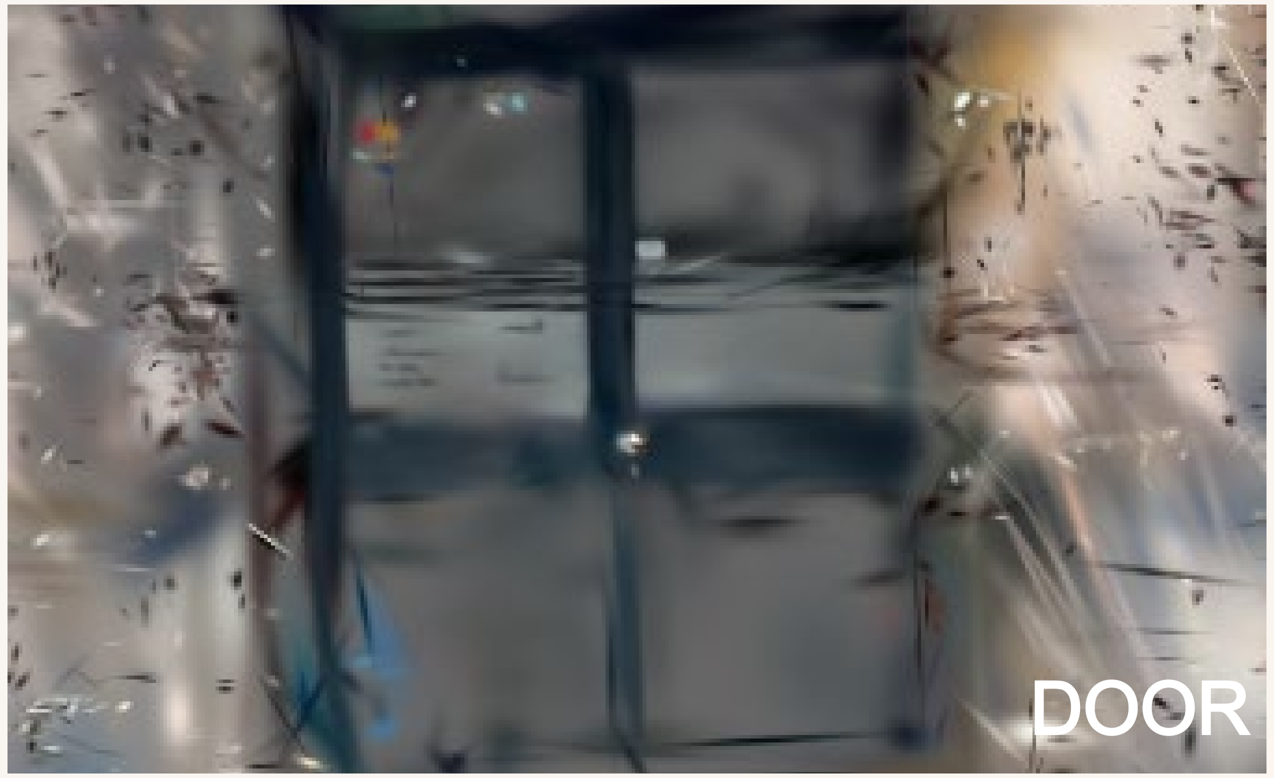
A clustering algorithm that groups data into clusters by minimizing distance within clusters, widely used for basic segmentation.

Segmentation

	SAM	K- means	GMM
Point Cloud			
Gaussian Splats			







LABELLING

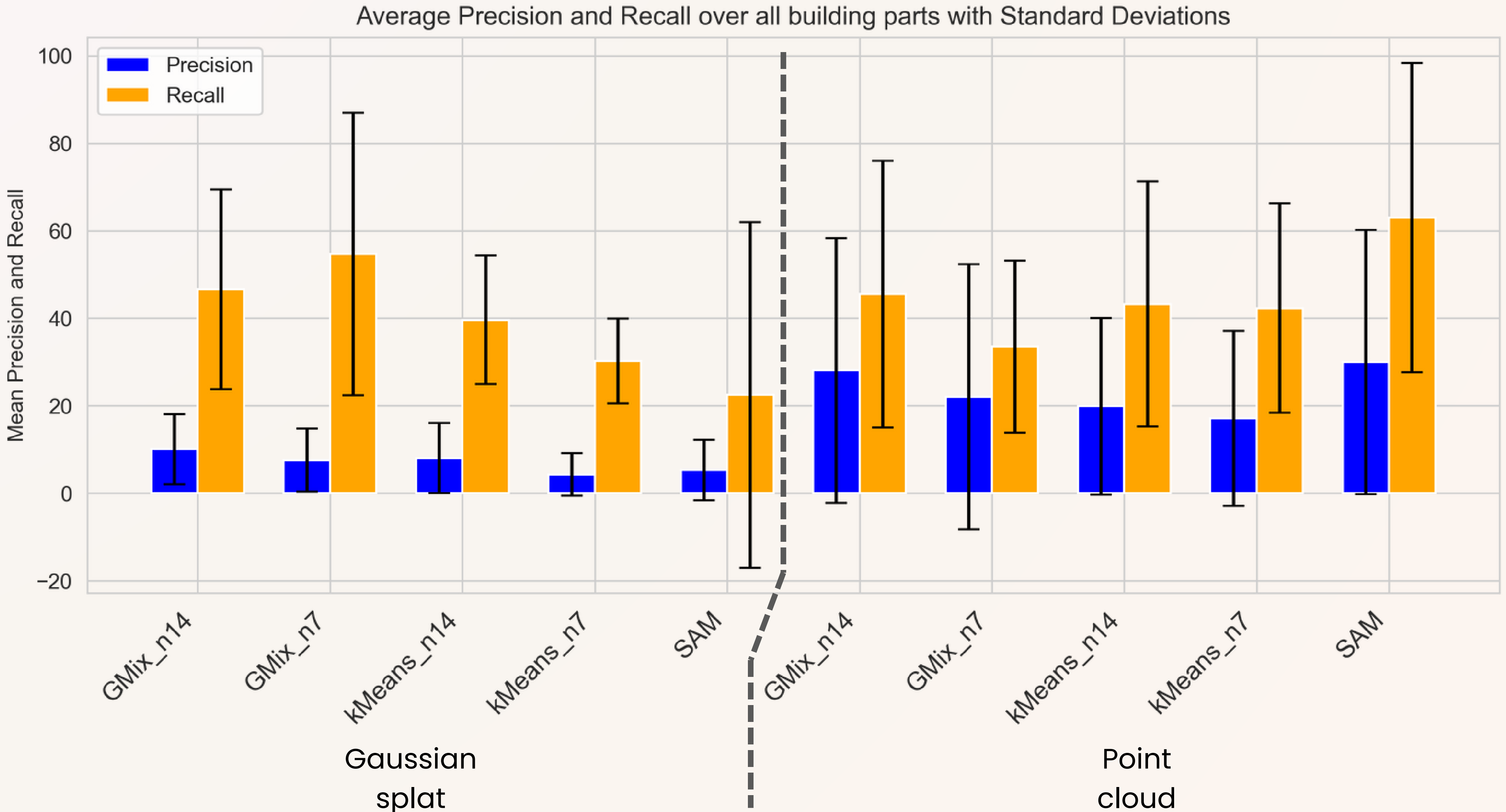
From the segments, we manually label the clusters based on IFC classes to match IFC model standards

PRECISION

For all points classified as a particular building part, how many of these points are accurately classified as that building part

RECALL

For all points that should be classified as a particular building part, how many are correctly classified as that building part



DISCUSSION

IFC model

- Structured data
- Interoperability
- Detailed architectural representation

Smart Guassian Splat

- Highest level of surface detail
- Hyper-realistic representation
- Only seperated by IFC classes

Smart Point Cloud

- High level of surface detail
- Semi-realistic representation
- Only seperated by IFC classes

CHANCES FOR IMPROVEMENT

Consider Segmenting Splats

Using whole splats instead of point centers for splat segmentation

Clearer Visualisation of Segments

Find a way to visualise spalts in an orderly manner

Advanced Segmentation Methods

Use deep learning segmentation methods

THANK YOU FOR LISTENING

Link to our Github can be found at :
https://github.com/ShawnTew/Synthesis-Project-Group-4