# MSc Project - Documentation

## Introduction

Robots that are expected to navigate efficiently through real-world environments need maps to localize themselves and plan actions. These maps just contain purely geometric information as the robot needs a semantic understanding of its surroundings to fulfill their tasks. In this project, we address the problem of object-based mapping for mobile robots in indoor environments. The goal of the project is to realize a mapping system where an occupancy representation of the scene is enhanced with object level semantics.

## Procedure

- ▼ **Input Data**
    - ▼ RGB , Depth images
    - ▼ Camera intrinsic matrix
    - ▼ TF transformations from camera frame to map frame for each image
    - ▼ Gradients containing probabilities for each pixel in the image. Obtained from ESANET.
- ▼ **Data Processing**
    - ▼ Information to note
        - ▼ let h, w represent height and width of image.
        - ▼ The images and TF transformation are of matching time stamps.
        - ▼ The gradients received from ESANET is having structure : [# of classes, h, w]
    - ▼ Data Arrays
        - ▼ **Image Pixel Coordinate Array**

- We create an array to contain the image pixel coordinates. The array is of shape:

  [h*w, 3]

  - where each entry in it will be :

    [i, j, 1]

    - where i and j represent the pixel coordinates, the final 1 is a place holder for the final z coordinate but currently this makes it a homogeneous pixel coordinate.

- **Depth Value Array**
  - We create an array to store the depth values from all the images. This array has shape:

    [# of images, h*w, 1]

    - The first dimension indicates the image number. This allows us to use the correct set of depth values for the correct RGB image.
    - The second dimension points to all the pixels in the image. We can see that this portion maps to the first dimension of the image pixel coordinate array.
    - The third dimension populates the depth values for the corresponding pixel coordinate.

- **Image Gradient Array**
  - The gradients mentioned here are the probability values we extract from the last layer of ESANET, just before its output layer.
    - For a single image, ESANET produces an array of shape

      [# of classes, h, w]

      for example SUNRGBD dataset has 37 label classes, in this case the output array shape will be:

      [37, h, w]

      (for some future examples we will consider the 37 as label number)
    - These gradients are stored and then loaded during the data processing. We store the gradients as an array of shape:

      [h*w, 37]

- ▼ where the first dimension will be mapped to the second dimension of the depth array and the first dimension of the image pixel array.

- ▼ Basically this mapping that is mentioned makes sure that the correct depth values and the correct probability gradients are assigned to the correct pixel coordinates.

## ▼ Algorithm

The following describes the steps involved involved in how we use the data mentioned in the previous section for our project.

### ▼ Transformation (image frame → camera frame [canonical])

- ▼ The image pixel coordinates we obtain from the image pixel coordinate array are currently in the image frame. These coordinates have to be transformed into the camera frame for our usage. To do this we use the camera intrinsic matrix. This gives us the pixel coordinates in the canonical camera frame. In this frame the z axis is in the direction of depth.

  [i, j, 1] → [x_canon_cam, y_canon_cam, 1]

  homogeneous

**Convert the pixel coordinates into camera rgb frame.**

(Currently the coordinates in this frame will be in canonical frame. we need to bring this into the camera frame)

```
camera_rgb_frame = (np.matmul(K_inv, pixels.T)).T # dimension [n,3]
```

### ▼ Depth Filtering

- ▼ Every depth sensor will have a maximum range. We found that for our depth sensor the maximum range is denoted as 5 meters. This means that every measurements beyond this 5 meter mark will be given the value of 5 meters. This can lead to false segmentation labels when we do further processing.

  To prevent this currently we filter out all the measurements that are beyond a threshold distance. For now we set this threshold distance as 4.5 meters.

### ▼ Multiply Depth

▼ Once we filter out the depth measurements, we proceed to the next step where we multiply the depth values to the corresponding pixel coordinates in the canonical camera frame.

▼ Once we multiply the depth we have each pixel with its depth in the canonical camera frame
[x, y, 1] canonical_homogeneous →[x, y, z]canonical

▼ **Transformation (camera frame[canonical] →camera frame)**

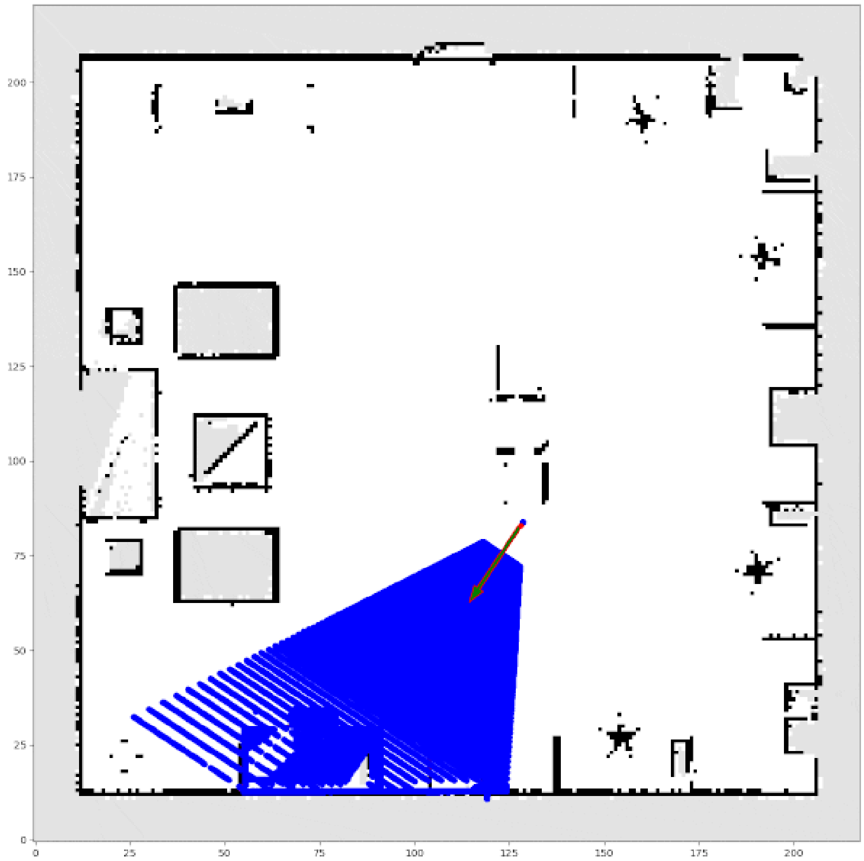
▼ We use the static transformation to transform the coordinates of the pixels in canonical frame into the camera frame.

**create matrix of transformation from canonical frame to camera frame**

```
roll = -1.571
pitch = 0.00
yaw = -1.571
translation = np.array([[0.00, 0.00, 0.00]]).T
H = homogenous(roll, pitch, yaw, translation)
```

▼ **Transformation (camera frame → map frame)**

▼ So no we have a set of point coordinates in the camera frame. Now we use the transformations from camera frame to the map frame for the corresponding time stamp from the TF transformations to project the points from the camera frame into the map frame.
Now we have a set of point clouds corresponding to each pixel in all images in the map frame. The following visualization was created using these point clouds.




- **Height Filtering**
  - An image contains everything that is within the view of the camera. As a result the semantic segmentation will contain the labels for every pixel that is observed within the view of the camera.
  - But when we look into the perspective of an occupancy grid it is create from the view of the lidar sensor. So in reality only the things that can be viewed from the perspective of the lidar will be seen in the occupancy grid map. So this means that all the pixels that belong to one column of an image will actually represent only one or part of a cell in the occupancy grid map.
  - So taking this information into consideration we filter out all the information that is outside a certain region around the optical axis of the lidar.

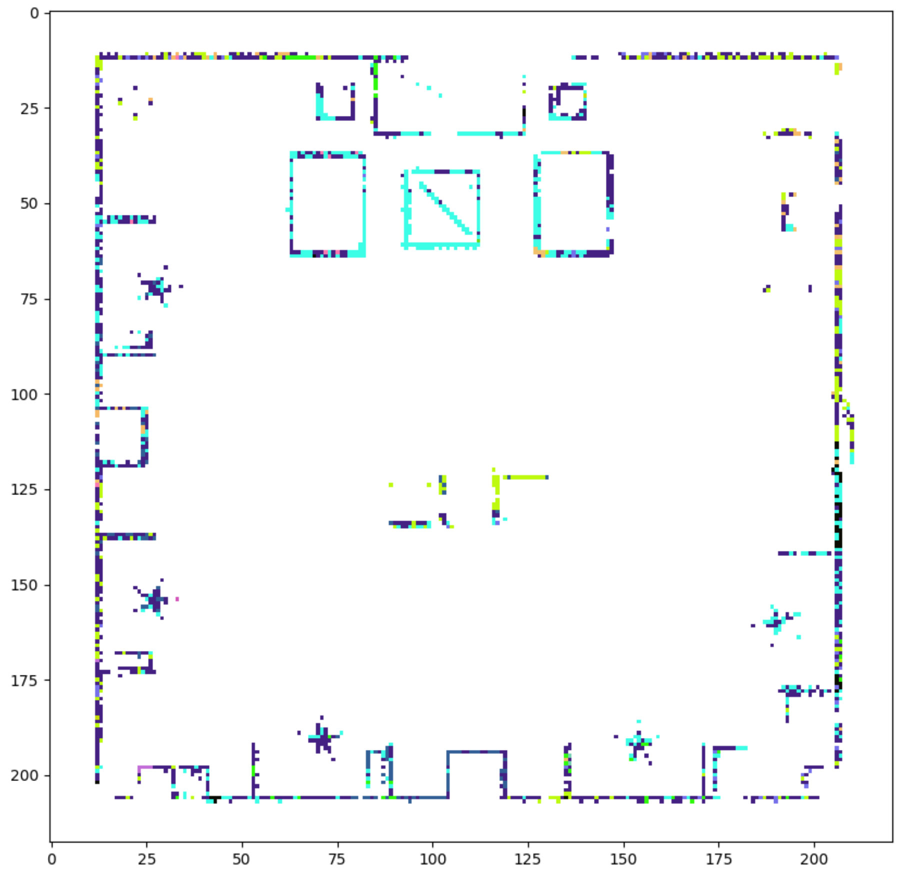
- Currently we set a region of 60cm height. All pixels when projected that lie outside the 60 cm height region are not considered when we assign the segmentation labels. The optical axis of the lidar for the robot we used lie approximately around the 10 cm height.

- **Assigning Probabilities**
  - In this step for each cell in the occupancy grid map we assign a certain semantic label based on all the observations that we obtained from the probability outputs of ESANET .
  - We have used mainly 4 different techniques to assign segmentation labels to the cells in the occupancy grid map.
    - Adding Probabilities
    - Adding Probabilities Normalized
    - Dependent Probabilities
    - Most Occurring Labels
  - Also we used 2 approaches in how we use these techniques to assign the semantic labels to the occupancy grid
    - Cell based Approach
    - Polygon Based Approach
  - These techniques and approaches will be described in detail in following sections.
- **Evaluation**
  - After the semantic labels are assigned to the occupancy grid, we evaluate the occupancy grid with a ground truth occupancy grid that we created by annotating the occupancy grid based on the RGB images.
  - We currently use the IOU metric to evaluate the different techniques and approaches.

- **Label Assignment Approaches**
  - **Cell Based**
    - In this approach, the smallest individual unit in the occupancy grid is considered to the the individual cells in the grid.

▼ We will use the different techniques for estimating the segmentation label for the cell.

▼ A sample output image for estimated semantic labels in a cell based approach is given below:

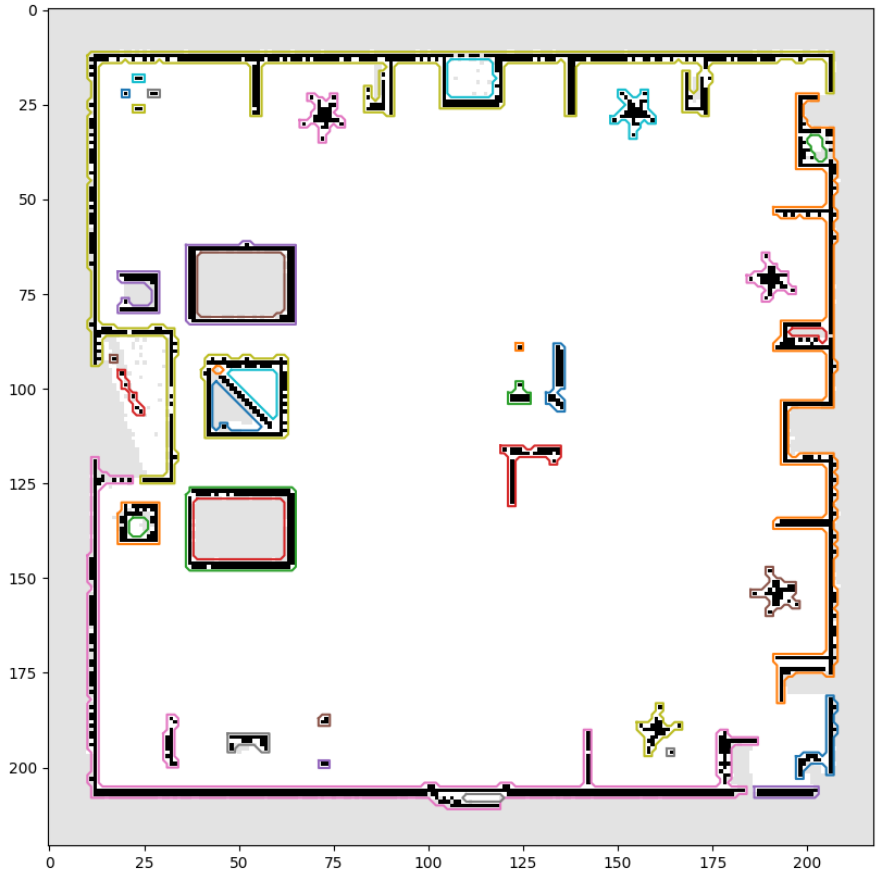



## ▼ Polygon Based

▼ In this approach we use the contours in the occupied regions to create polygons in the occupancy grid map.

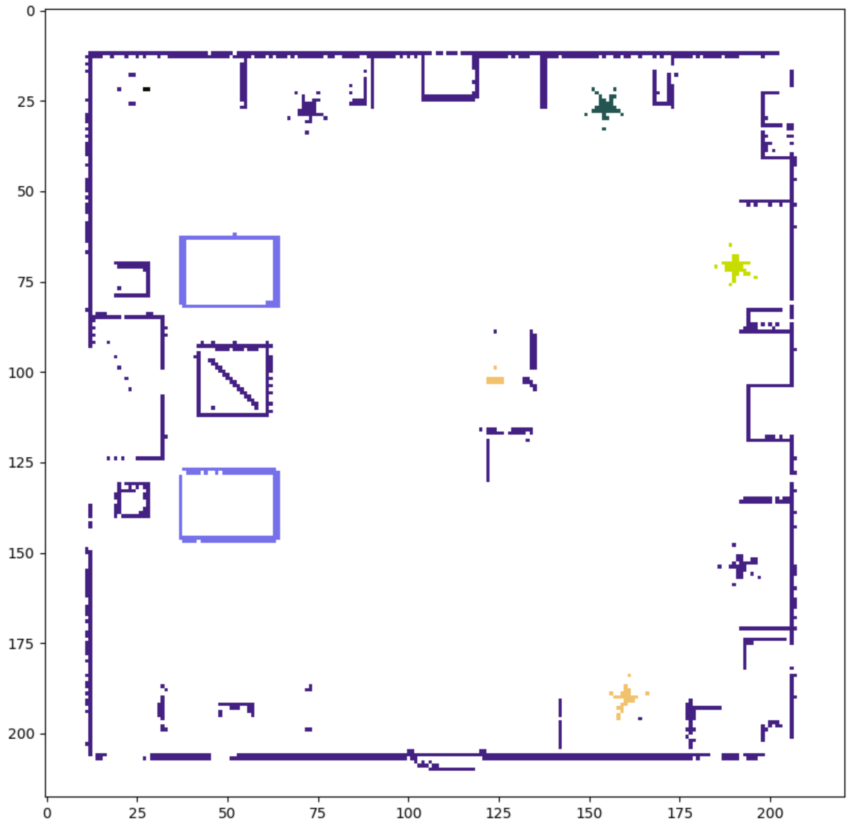
▼ We assume that these individual polygons represent individual objects in the map. This assumption holds true unless we have situations where the objects are placed touching each other or placed one in front of other. For example cabinets kept in front of a wall will be seen as part of the wall itself in the perspective of the occupancy grid map.

▼ The following image shows polygons created from the occupancy grid map:




▼ Now we consider these polygons as the smallest individual units in the occupancy grid map. Then use the techniques to estimate a label for each polygon as a whole.

▼ Then this semantic label is assigned to all the cells present within the polygon. The following image is a sample output from polygon based approach




▼ **Label Estimation Techniques**

▼ **Adding Probabilities**

▼ For a given unit (cell or polygon) in the occupancy grid each observation that we get will be a list of probabilities. If we consider SUNRGBD, then we will have a list of 37 probabilities, where each individual probability represents the probability for that unit to belong to a certain semantic label.

obs  = [ P(label1), …, P(label37) ]

with:

sum(obs) = 1

▼ When a new observation is obtained for the same cell, we perform element wise addition of the new probabilities with the new probabilities. This will become the new observation for the cell. This process is continued until we have gone through all the observation data. At the end we have,

cell_obs =$sigma_1^N(obs(i))$

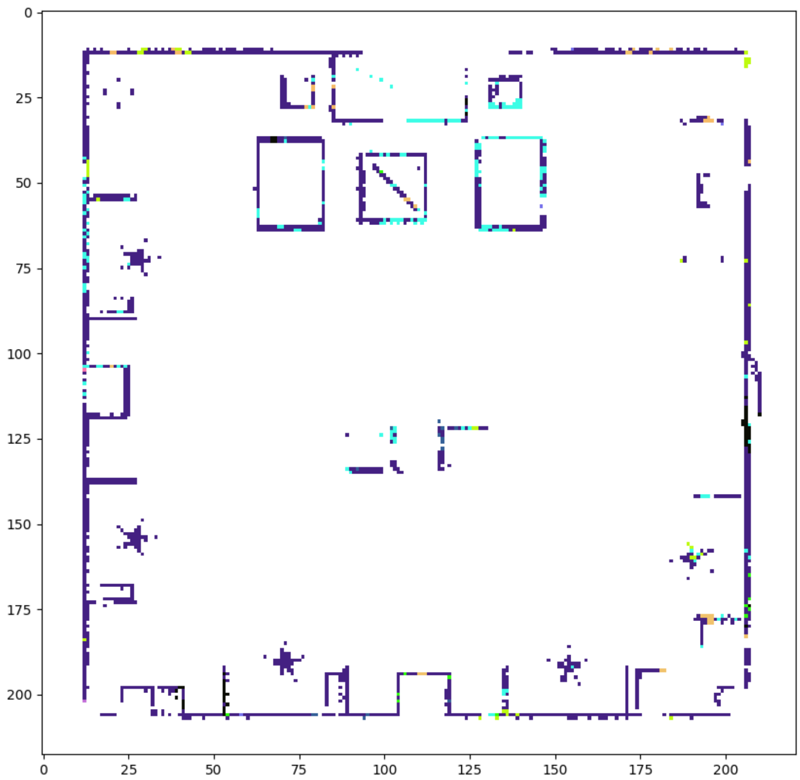
where, i is the observation number. The summation operation is always performed element wise. That is,

cell_obs = [ P(old_label1) + P(new_label1), ….., P(old_label37) + P(new_label37) ]

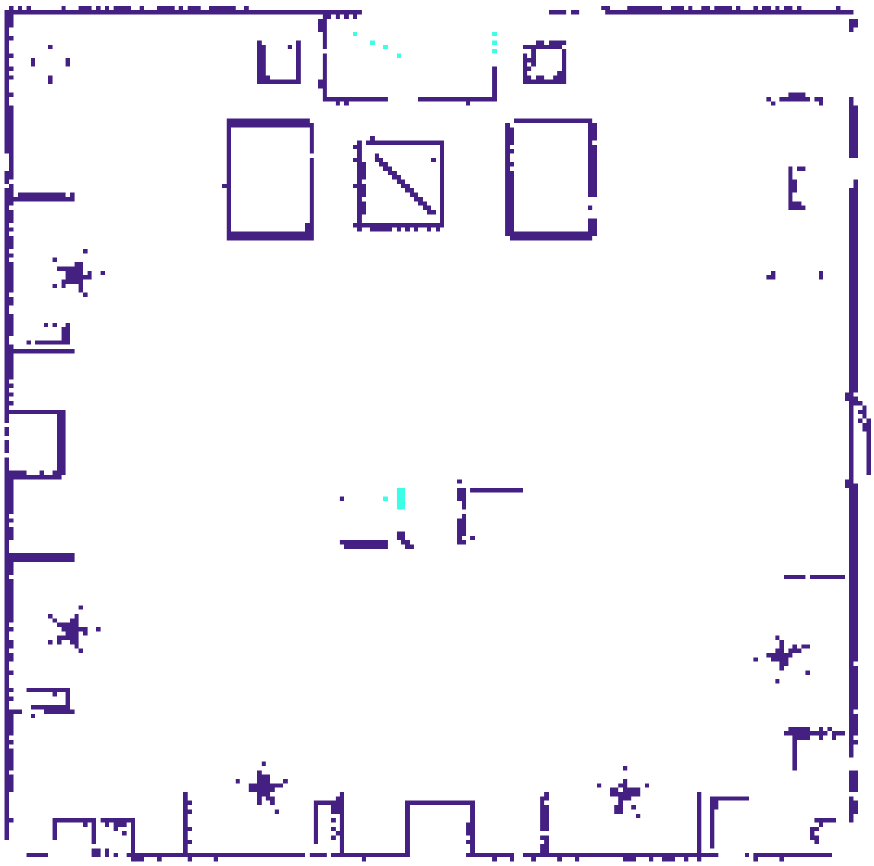
- After we have gone through all the observation data we perform a softmax over the probability observations of each unit and use the semantic label which has the highest probability.

cell_obs = argmax(softmax( cell_obs))

- The following are the outputs for this technique for the cell based and polygon based approaches.
    - Cell Based Approach



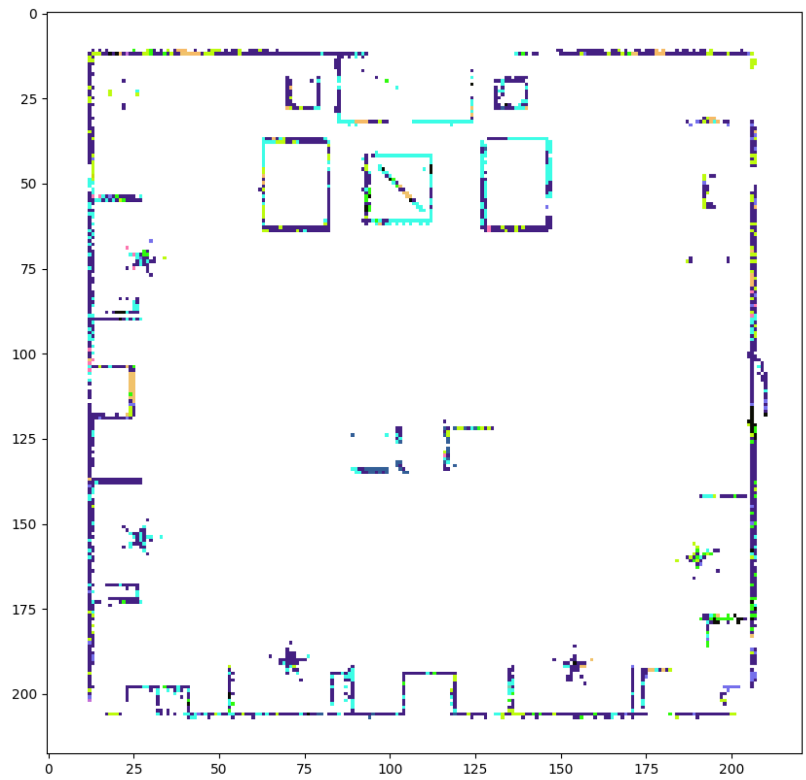

- Polygon Based Approach



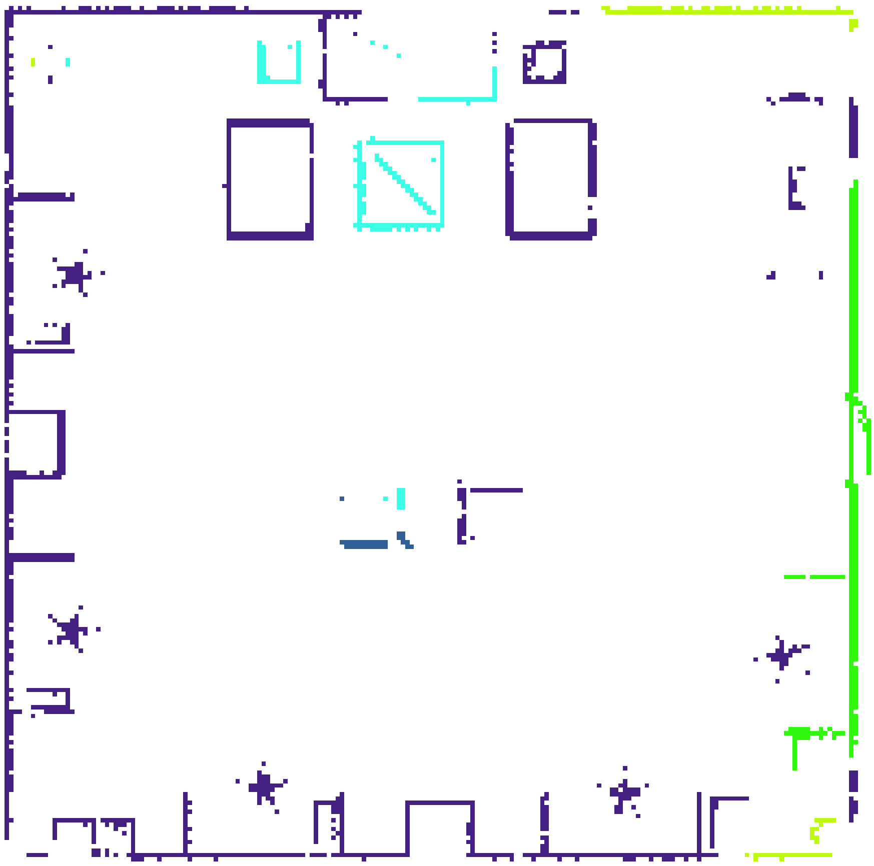
- **Adding Probabilities Normalized**
  - This method is a slightly modified version of the previous technique.
  - For the first observation of a unit (cell or polygon) we keep them as the initial estimate of the unit.
  - When the new observations are obtained we similarly does the element wise addition of probabilities stated earlier. But if we look at this step we can see that after we add the new probabilities, the sum changes, that is:
    cell_obs = [ P(old_label1) + P(new_label1), ….., P(old_label37) + P(new_label37) ]
    Now if we check sum we see that:
    sum(cell_obs) > 1
    So we normalize the cell probabilities after a new observation is added by:
    cell_obs = cell_obs / sum(cell_obs)
    this ensures sum(cell_obs) = 1 before a new observation is added.
  - The remaining steps are the same as the previous technique.

▼ The following are the results obtained by this technique for the cell based and polygon based approaches.

▼ Cell based approach




▼ Polygon based approach



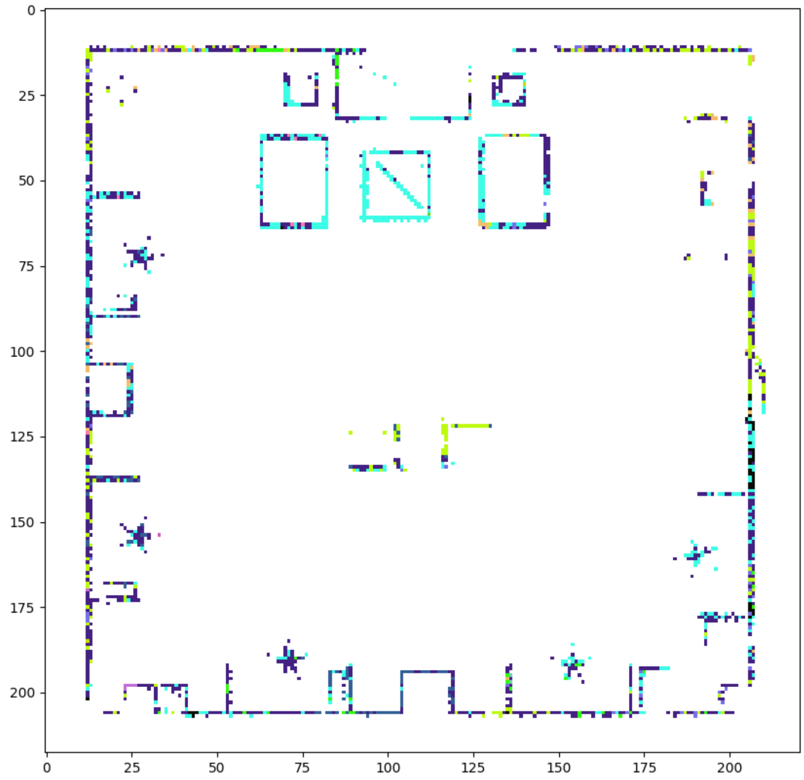
- **Dependent Probabilities**
  - In this technique, we utilize the theory of dependent probabilities to find the best matching semantic label for the cell or polygon.
  - Since each consequent observations are for the same cell or polygon, we can consider these as dependent events.
  - The first observation will become the initial probability for the cell or polygon. Lets call this P(A). P(A) will be the list of 37 probabilities for all label classes in case of SUNRGBD.
  - The new observation will be called as P(B).
  - Now since we consider P(A) and P(B) as dependent, we try to calculate the probability of A given our newly observed probabilities B. This can be written as:

    $$P(A \mid B) = P(A \text{ and } B) / P(B)$$

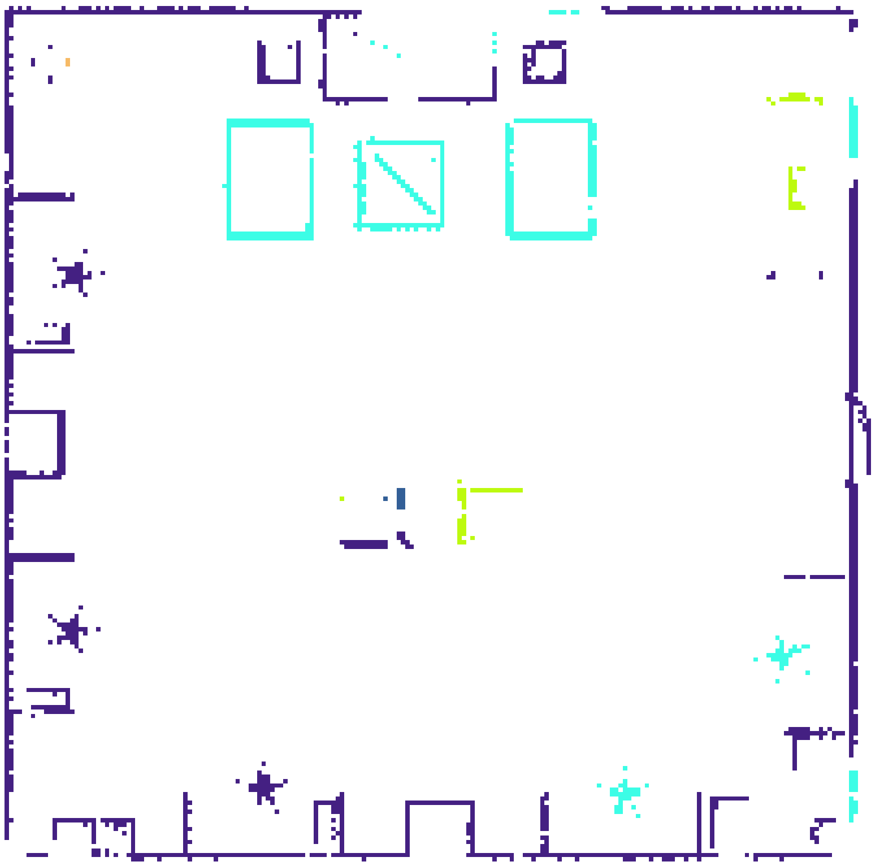
    with

    $$P(A \text{ and } B) = P(A) * P(B)$$

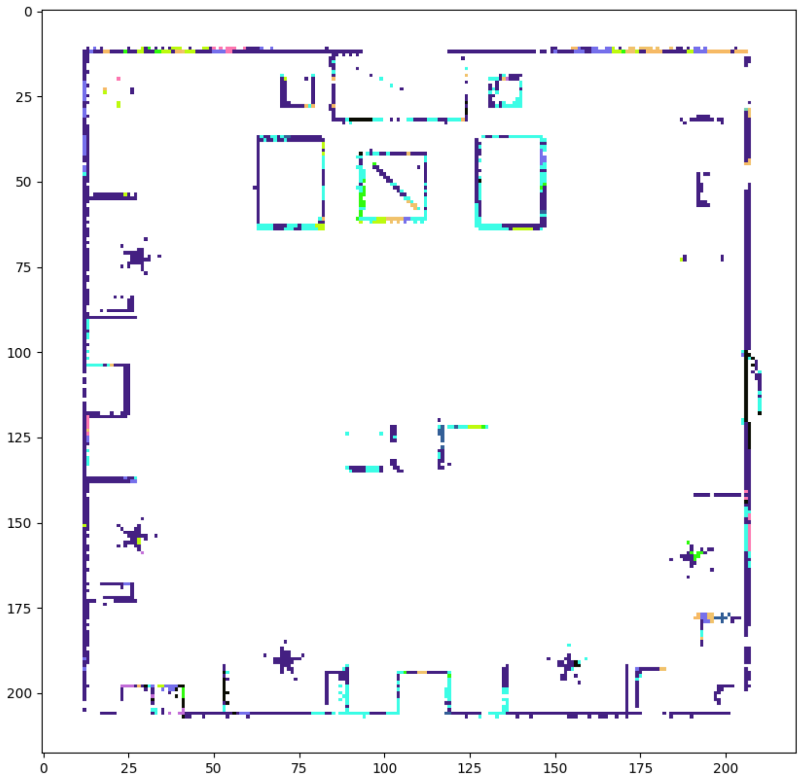
- ▼ This is continued for all the new observations that we get. At the end we take the label which has the highest probability as the semantic label for that cell or polygon.
- ▼ The following are the outputs we obtained using this technique for the cell based and polygon based approaches.
  - ▼ Cell based approach



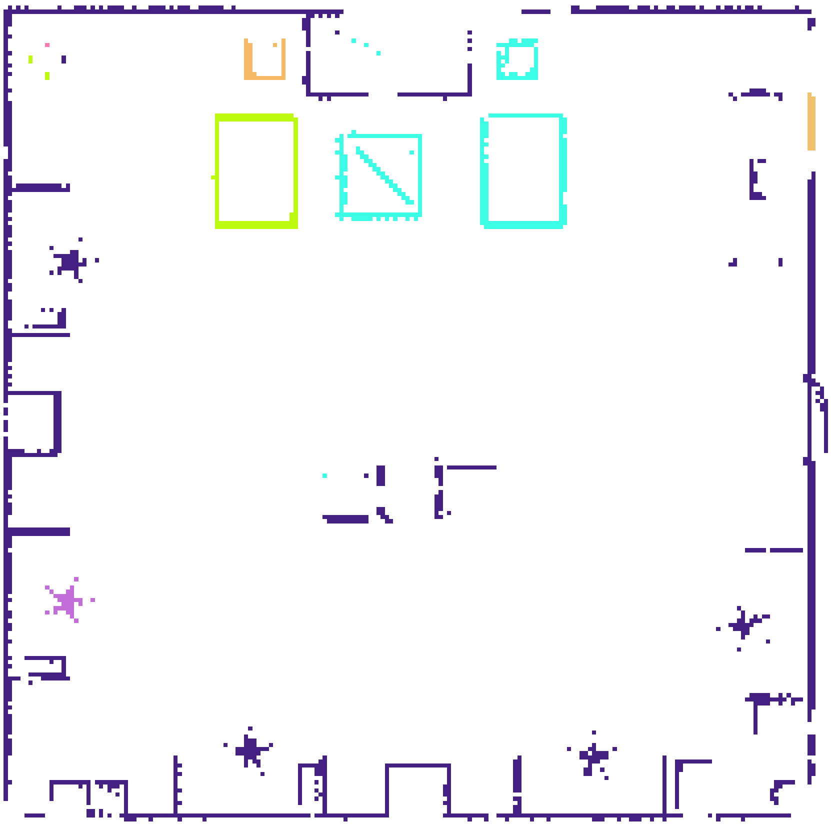

  - ▼ Polygon based approach



- **Most Occurring Labels**
  - This is a fairly straightforward strategy,
    For any given cell or polygon, as each observations are obtained we create a list of the label with the highest probability in each individual observation.
  - At the end we choose the label in the list which occurs the most and assign that label as the semantic label for the cell or polygon.
  - The following are the outputs we received using this technique for the cell based and polygon based approaches.
    - Cell based approach

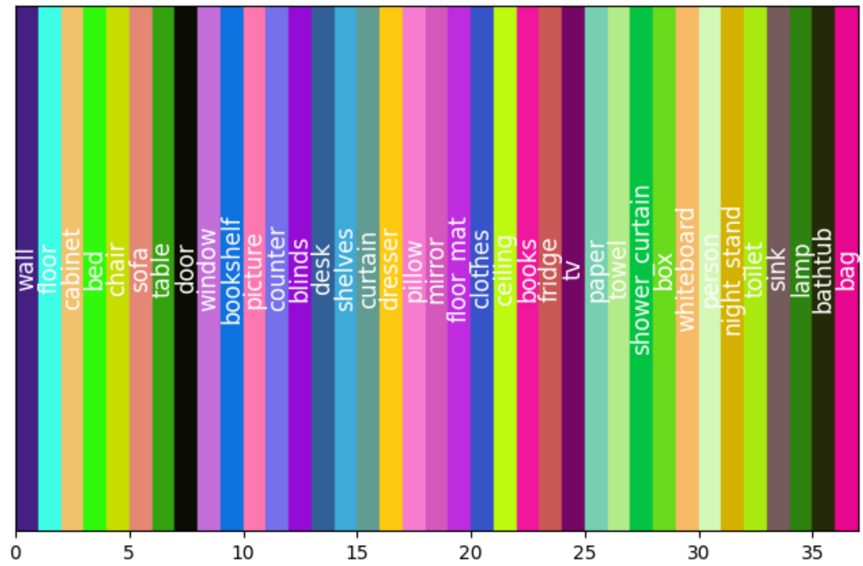



▼ Polygon based approach

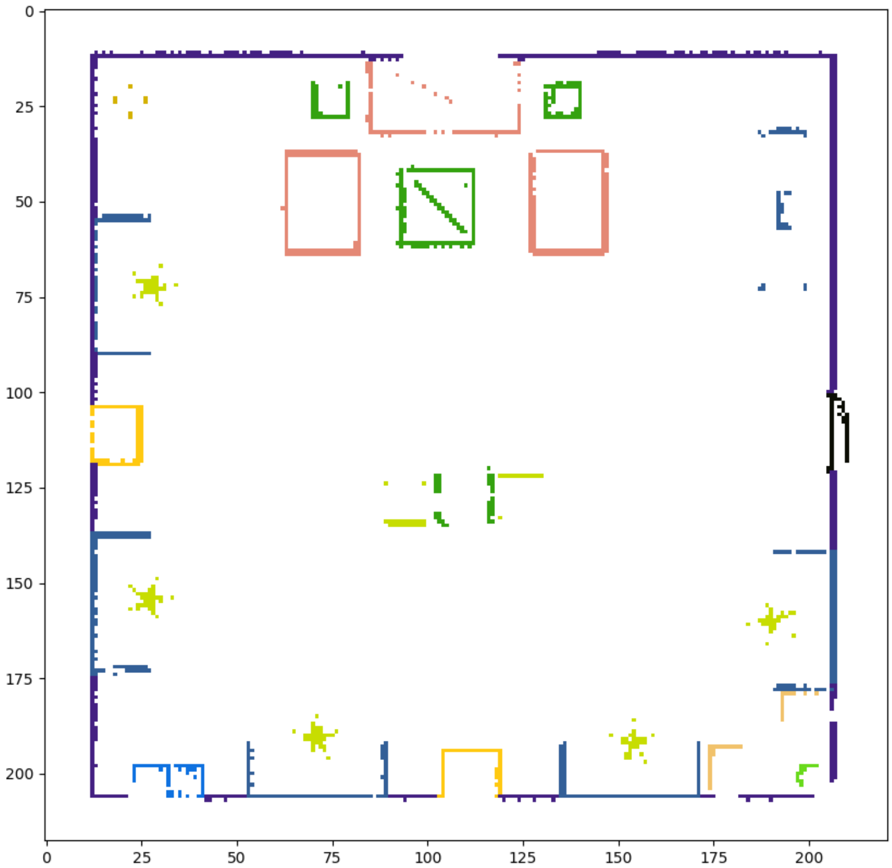


▼ **Evaluation**

- ▼ This section looks at the evaluation metrics we currently use.\
- ▼ We are using the Intersection Over Union (IOU) metric to evaluate our current results.
- ▼ To achieve this we first created a ground truth occupancy grid map with semantic labels by performing annotation by comparing with the scenes visible in the RGB images.
- ▼ Semantic labels colors SUNRGBD




▼ Ground truth occupancy grid map




# Evaluation Results

## Cell Based Approach

- ▼ **Adding probabilities**

  label with highest iou: wall

  Highest iou: 0.28660287081339714

  - ▼ **All Values:**

    label: wall
    iou: 0.28660287081339714
    union: 2090 pixels
    intersection: 599 pixels

label: floor
iou: 0.0
union: 200 pixels
intersection: 0 pixels
label: cabinet
iou: 0.07407407407407407
union: 54 pixels
intersection: 4 pixels
label: bed
iou: 0.0
union: 12 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 190 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0
union: 297 pixels
intersection: 0 pixels
label: door
iou: 0.10112359550561797
union: 89 pixels
intersection: 9 pixels
label: window
iou: 0.0
union: 1 pixels
intersection: 0 pixels
label: bookshelf
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: picture
iou: 0.0

union: 1 pixels
intersection: 0 pixels
label: counter
iou: 0.0
union: 4 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.004123711340206186
union: 485 pixels
intersection: 2 pixels
label: shelves
iou: 0.0
union: 1 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: dresser
iou: 0.0
union: 46095 pixels
intersection: 0 pixels
label: pillow
iou: nan
union: 0 pixels
intersection: 0 pixels
label: mirror
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: floor_mat
iou: 0.0
union: 50 pixels
intersection: 0 pixels

label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 297 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: 0.0
union: 17 pixels
intersection: 0 pixels
label: paper
iou: 0.0
union: 5 pixels
intersection: 0 pixels
label: towel
iou: nan
union: 0 pixels
intersection: 0 pixels
label: shower_curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: box
iou: 0.0
union: 13 pixels
intersection: 0 pixels
label: whiteboard
iou: 0.0

union: 17 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: toilet
iou: 0.0
union: 12 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bathtub
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bag
iou: nan
union: 0 pixels
intersection: 0 pixels

▼ **Adding Probabilities Normalized**

label with highest iou: wall

Highest iou: 0.26810747663551404

▼ **All values**

label: wall
iou: 0.26810747663551404

union: 1712 pixels
intersection: 459 pixels
label: floor
iou: 0.0
union: 403 pixels
intersection: 0 pixels
label: cabinet
iou: 0.04
union: 75 pixels
intersection: 3 pixels
label: bed
iou: 0.0
union: 74 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 191 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0
union: 423 pixels
intersection: 0 pixels
label: door
iou: 0.08235294117647059
union: 85 pixels
intersection: 7 pixels
label: window
iou: 0.0
union: 2 pixels
intersection: 0 pixels
label: bookshelf
iou: 0.0
union: 50 pixels
intersection: 0 pixels

label: picture
iou: 0.0
union: 16 pixels
intersection: 0 pixels
label: counter
iou: 0.0
union: 55 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.003937007874015748
union: 508 pixels
intersection: 2 pixels
label: shelves
iou: 0.0
union: 2 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: dresser
iou: 0.0
union: 46095 pixels
intersection: 0 pixels
label: pillow
iou: nan
union: 0 pixels
intersection: 0 pixels
label: mirror
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: floor_mat
iou: 0.0

union: 50 pixels
intersection: 0 pixels
label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 423 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: 0.0
union: 31 pixels
intersection: 0 pixels
label: paper
iou: 0.0
union: 70 pixels
intersection: 0 pixels
label: towel
iou: nan
union: 0 pixels
intersection: 0 pixels
label: shower_curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: box
iou: 0.0
union: 13 pixels
intersection: 0 pixels

label: whiteboard
iou: 0.0
union: 31 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: toilet
iou: 0.0
union: 74 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bathtub
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bag
iou: nan
union: 0 pixels
intersection: 0 pixels

▼ **Dependent Probabilities**

▼ label with highest iou: wall

Highest iou: 0.22774193548387098

▼ **All values**

label: wall
iou: 0.22774193548387098
union: 1550 pixels
intersection: 353 pixels
label: floor
iou: 0.0
union: 582 pixels
intersection: 0 pixels
label: cabinet
iou: 0.0
union: 61 pixels
intersection: 0 pixels
label: bed
iou: 0.0
union: 46 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 192 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0
union: 458 pixels
intersection: 0 pixels
label: door
iou: 0.06097560975609756
union: 82 pixels
intersection: 5 pixels
label: window
iou: 0.0
union: 6 pixels
intersection: 0 pixels
label: bookshelf
iou: 0.0

union: 50 pixels
intersection: 0 pixels
label: picture
iou: 0.0
union: 10 pixels
intersection: 0 pixels
label: counter
iou: 0.0
union: 60 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.06126126126126126
union: 555 pixels
intersection: 34 pixels
label: shelves
iou: 0.0
union: 6 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: dresser
iou: 0.0
union: 46095 pixels
intersection: 0 pixels
label: pillow
iou: nan
union: 0 pixels
intersection: 0 pixels
label: mirror
iou: 0.0
union: 8 pixels
intersection: 0 pixels

label: floor_mat
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 458 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: 0.0
union: 37 pixels
intersection: 0 pixels
label: paper
iou: 0.0
union: 68 pixels
intersection: 0 pixels
label: towel
iou: nan
union: 0 pixels
intersection: 0 pixels
label: shower_curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: box
iou: 0.0

union: 14 pixels
intersection: 0 pixels
label: whiteboard
iou: 0.0
union: 37 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 8 pixels
intersection: 0 pixels
label: toilet
iou: 0.0
union: 46 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bathtub
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bag
iou: nan
union: 0 pixels
intersection: 0 pixels

▼ **Most Occurring Label**

- ▼ label with highest iou: wall
- ▼ Highest iou: 0.30120481927710846

▼ **All values**

label: wall
iou: 0.30120481927710846
union: 1826 pixels
intersection: 550 pixels
label: floor
iou: 0.0
union: 353 pixels
intersection: 0 pixels
label: cabinet
iou: 0.05405405405405406
union: 74 pixels
intersection: 4 pixels
label: bed
iou: 0.0
union: 34 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 190 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0
union: 306 pixels
intersection: 0 pixels
label: door
iou: 0.2608695652173913
union: 92 pixels
intersection: 24 pixels
label: window
iou: 0.0
union: 11 pixels
intersection: 0 pixels
label: bookshelf

iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: picture
iou: 0.0
union: 27 pixels
intersection: 0 pixels
label: counter
iou: 0.0
union: 86 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.010224948875255624
union: 489 pixels
intersection: 5 pixels
label: shelves
iou: 0.0
union: 11 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: dresser
iou: 0.0
union: 46035 pixels
intersection: 0 pixels
label: pillow
iou: nan
union: 0 pixels
intersection: 0 pixels
label: mirror
iou: 0.0
union: 7 pixels

intersection: 0 pixels
label: floor_mat
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 306 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: 0.0
union: 35 pixels
intersection: 0 pixels
label: paper
iou: 0.0
union: 112 pixels
intersection: 0 pixels
label: towel
iou: nan
union: 0 pixels
intersection: 0 pixels
label: shower_curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: box

iou: 0.0
union: 13 pixels
intersection: 0 pixels
label: whiteboard
iou: 0.0
union: 35 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: toilet
iou: 0.0
union: 34 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bathtub
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bag
iou: nan
union: 0 pixels
intersection: 0 pixels

### Polygon Based Approach

▼ **Adding probabilities**

label with highest iou: wall

Highest iou: 0.28862478777589134

▼ **All Values:**

label: wall
iou: 0.28862478777589134
union: 2356 pixels
intersection: 680 pixels
label: floor
iou: 0.0
union: 18 pixels
intersection: 0 pixels
label: cabinet
iou: 0.0
union: 35 pixels
intersection: 0 pixels
label: bed
iou: nan
union: 0 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 190 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0
union: 257 pixels
intersection: 0 pixels
label: door
iou: 0.0
union: 46 pixels
intersection: 0 pixels
label: window

iou: nan
union: 0 pixels
intersection: 0 pixels
label: bookshelf
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: picture
iou: nan
union: 0 pixels
intersection: 0 pixels
label: counter
iou: nan
union: 0 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.0
union: 472 pixels
intersection: 0 pixels
label: shelves
iou: nan
union: 0 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: dresser
iou: 0.0
union: 46095 pixels
intersection: 0 pixels
label: pillow
iou: nan
union: 0 pixels

intersection: 0 pixels
label: mirror
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: floor_mat
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 257 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: nan
union: 0 pixels
intersection: 0 pixels
label: paper
iou: nan
union: 0 pixels
intersection: 0 pixels
label: towel
iou: nan
union: 0 pixels
intersection: 0 pixels
label: shower_curtain

iou: nan
union: 0 pixels
intersection: 0 pixels
label: box
iou: 0.0
union: 13 pixels
intersection: 0 pixels
label: whiteboard
iou: nan
union: 0 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: toilet
iou: nan
union: 0 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bathtub
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bag
iou: nan

union: 0 pixels
intersection: 0 pixels

▼ **Adding Probabilities Normalized**

label with highest iou: wall

Highest iou: 0.21377551020408164

▼ **All values**

label: wall
iou: 0.21377551020408164
union: 1960 pixels
intersection: 419 pixels
label: floor
iou: 0.0
union: 209 pixels
intersection: 0 pixels
label: cabinet
iou: 0.0
union: 35 pixels
intersection: 0 pixels
label: bed
iou: 0.0
union: 310 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 190 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0
union: 383 pixels
intersection: 0 pixels
label: door
iou: 0.0

union: 46 pixels
intersection: 0 pixels
label: window
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bookshelf
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: picture
iou: nan
union: 0 pixels
intersection: 0 pixels
label: counter
iou: nan
union: 0 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.0
union: 502 pixels
intersection: 0 pixels
label: shelves
iou: nan
union: 0 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: dresser
iou: 0.0
union: 46095 pixels
intersection: 0 pixels

label: pillow
iou: nan
union: 0 pixels
intersection: 0 pixels
label: mirror
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: floor_mat
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 383 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: nan
union: 0 pixels
intersection: 0 pixels
label: paper
iou: nan
union: 0 pixels
intersection: 0 pixels
label: towel
iou: nan

union: 0 pixels
intersection: 0 pixels
label: shower_curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: box
iou: 0.0
union: 13 pixels
intersection: 0 pixels
label: whiteboard
iou: nan
union: 0 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: toilet
iou: 0.0
union: 310 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bathtub
iou: nan
union: 0 pixels
intersection: 0 pixels

label: bag
iou: nan
union: 0 pixels
intersection: 0 pixels

▼ **Dependent Probabilities**

▼ label with highest iou: wall

Highest iou: 0.34428024083196496

▼ **All values**

label: wall
iou: 0.34428024083196496
union: 1827 pixels
intersection: 629 pixels
label: floor
iou: 0.0
union: 514 pixels
intersection: 0 pixels
label: cabinet
iou: 0.0
union: 35 pixels
intersection: 0 pixels
label: bed
iou: nan
union: 0 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 190 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0
union: 307 pixels
intersection: 0 pixels

label: door
iou: 0.0
union: 46 pixels
intersection: 0 pixels
label: window
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bookshelf
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: picture
iou: nan
union: 0 pixels
intersection: 0 pixels
label: counter
iou: nan
union: 0 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.0
union: 483 pixels
intersection: 0 pixels
label: shelves
iou: nan
union: 0 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: dresser
iou: 0.0

union: 46095 pixels
intersection: 0 pixels
label: pillow
iou: nan
union: 0 pixels
intersection: 0 pixels
label: mirror
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: floor_mat
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 307 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: 0.0
union: 2 pixels
intersection: 0 pixels
label: paper
iou: nan
union: 0 pixels
intersection: 0 pixels

label: towel
iou: nan
union: 0 pixels
intersection: 0 pixels
label: shower_curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: box
iou: 0.0
union: 13 pixels
intersection: 0 pixels
label: whiteboard
iou: 0.0
union: 2 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: toilet
iou: nan
union: 0 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bathtub
iou: nan

union: 0 pixels
intersection: 0 pixels
label: bag
iou: nan
union: 0 pixels
intersection: 0 pixels

▼ **Most Occurring Label**

▼ label with highest iou: wall

Highest iou: 0.3566017316017316

▼ **All values**

label: wall
iou: 0.3566017316017316
union: 1848 pixels
intersection: 659 pixels
label: floor
iou: 0.0
union: 332 pixels
intersection: 0 pixels
label: cabinet
iou: 0.0
union: 62 pixels
intersection: 0 pixels
label: bed
iou: nan
union: 0 pixels
intersection: 0 pixels
label: chair
iou: 0.0
union: 190 pixels
intersection: 0 pixels
label: sofa
iou: 0.0
union: 360 pixels
intersection: 0 pixels
label: table
iou: 0.0

union: 391 pixels
intersection: 0 pixels
label: door
iou: 0.0
union: 46 pixels
intersection: 0 pixels
label: window
iou: 0.0
union: 33 pixels
intersection: 0 pixels
label: bookshelf
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: picture
iou: 0.0
union: 1 pixels
intersection: 0 pixels
label: counter
iou: nan
union: 0 pixels
intersection: 0 pixels
label: blinds
iou: nan
union: 0 pixels
intersection: 0 pixels
label: desk
iou: 0.0
union: 472 pixels
intersection: 0 pixels
label: shelves
iou: 0.0
union: 33 pixels
intersection: 0 pixels
label: curtain
iou: nan
union: 0 pixels
intersection: 0 pixels

label: dresser
iou: 0.0
union: 46077 pixels
intersection: 0 pixels
label: pillow
iou: nan
union: 0 pixels
intersection: 0 pixels
label: mirror
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: floor_mat
iou: 0.0
union: 50 pixels
intersection: 0 pixels
label: clothes
iou: nan
union: 0 pixels
intersection: 0 pixels
label: ceiling
iou: 0.0
union: 391 pixels
intersection: 0 pixels
label: books
iou: nan
union: 0 pixels
intersection: 0 pixels
label: fridge
iou: nan
union: 0 pixels
intersection: 0 pixels
label: tv
iou: 0.0
union: 38 pixels
intersection: 0 pixels
label: paper
iou: 0.0

union: 1 pixels
intersection: 0 pixels
label: towel
iou: nan
union: 0 pixels
intersection: 0 pixels
label: shower_curtain
iou: nan
union: 0 pixels
intersection: 0 pixels
label: box
iou: 0.0
union: 13 pixels
intersection: 0 pixels
label: whiteboard
iou: 0.0
union: 38 pixels
intersection: 0 pixels
label: person
iou: nan
union: 0 pixels
intersection: 0 pixels
label: night_stand
iou: 0.0
union: 7 pixels
intersection: 0 pixels
label: toilet
iou: nan
union: 0 pixels
intersection: 0 pixels
label: sink
iou: nan
union: 0 pixels
intersection: 0 pixels
label: lamp
iou: nan
union: 0 pixels
intersection: 0 pixels

label: bathtub
iou: nan
union: 0 pixels
intersection: 0 pixels
label: bag
iou: nan
union: 0 pixels
intersection: 0 pixels

# Evaluation Summary

### Highest IOU

### Cell Based

| **Technique** | **IOU** |
| --- | --- |
| Adding probabilities | 0.28660287081339714 |
| Adding Probabilities Normalized | 0.26810747663551404 |
| Dependent Probabilities | 0.22774193548387098 |
| Most Occurring Label | 0.30120481927710846 |

### Polygon Based

| **Technique** | **IOU** |
| --- | --- |
| Adding probabilities | 0.28862478777589134 |
| Adding Probabilities Normalized | 0.21377551020408164 |
| Dependent Probabilities | 0.34428024083196496 |
| Most Occurring Label | 0.3566017316017316 |

The technique that performed the best when looking at IOU is **Most Occurring Labels** in both cell based and polygon based approaches.