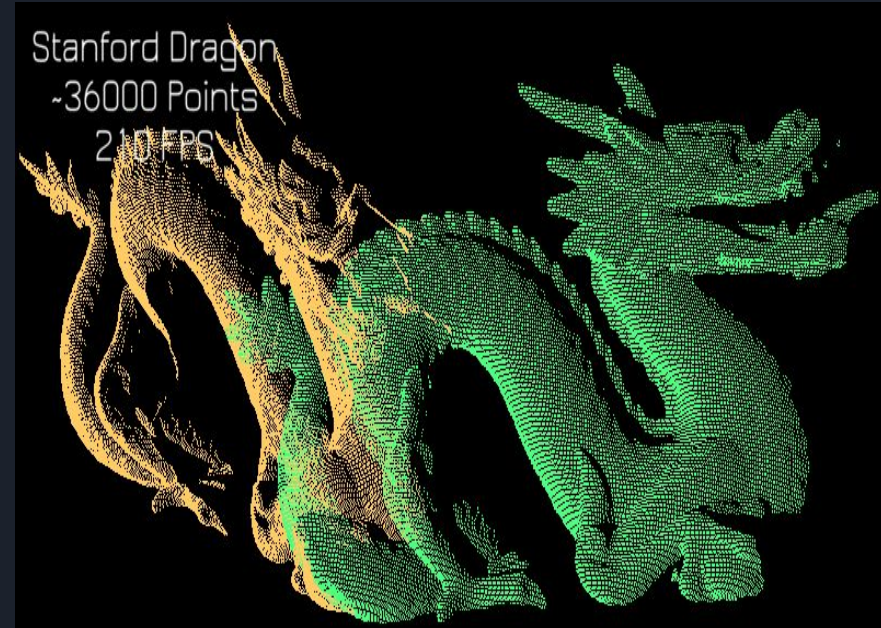


# 3D Point Cloud Registration using Gaussian Mixture Models

Srinath Rajagopalan, Somanshu Agarwal, Dhruv Karthik

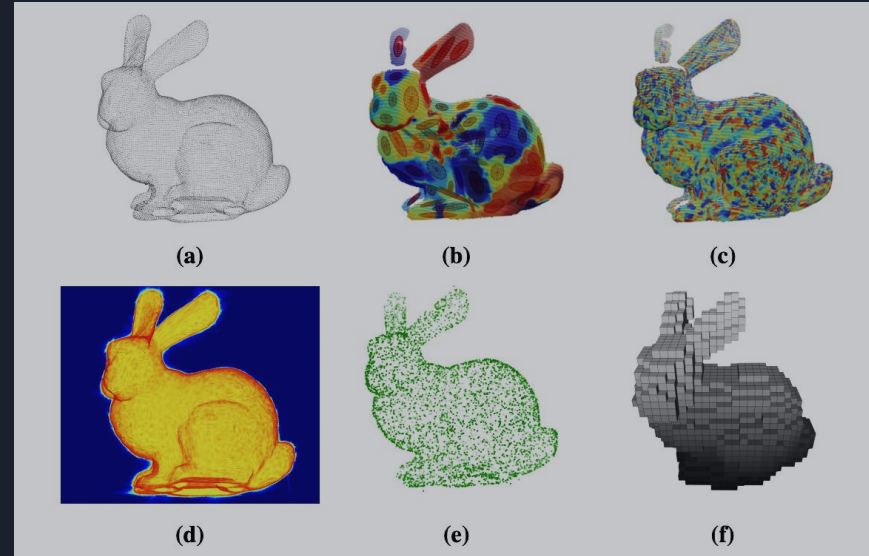
# Point Cloud Registration

- Point Cloud Registration (PCR) is the task of aligning two or more point clouds by estimating the relative transformation between them.
- PCR is extensively used in the computer vision and robotics for 3D object mapping, SLAM, dense reconstruction, 3D pose estimation.



# Why Probabilistic Representation?

- Deal with outliers and noise
- Continuous geometry - representation is differentiable!
- Avoids artifacts introduced by discretization
- Re-sampling, Heat Maps, Occupancy Grid Maps



Source - [Eckart et al 2016](#)

# Gaussian Mixture Models - 2D

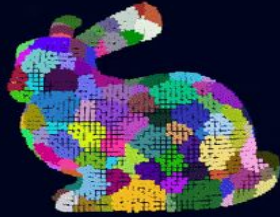
GMM GPU



GMM GPU



# Gaussian Mixture Models - 3D

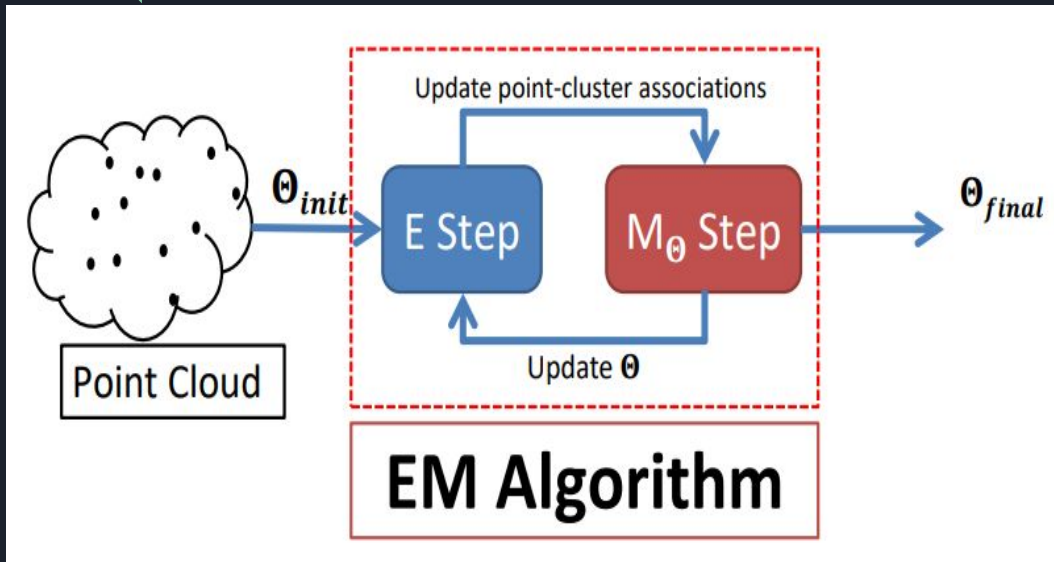


**100 GMM Components**



**800 GMM Components**

# Expectation-Maximization Algorithm



- Point Cloud Data is fed as input to the EM algorithm with some parameter initializations.
- Algorithm iteratively updates point-cluster associations and the parameters.
- When convergence is reached, the final parameters can be used to model the Point Cloud Data.

Source: [NVIDIA - Accelerating GMMs on 3D Point Cloud](#)

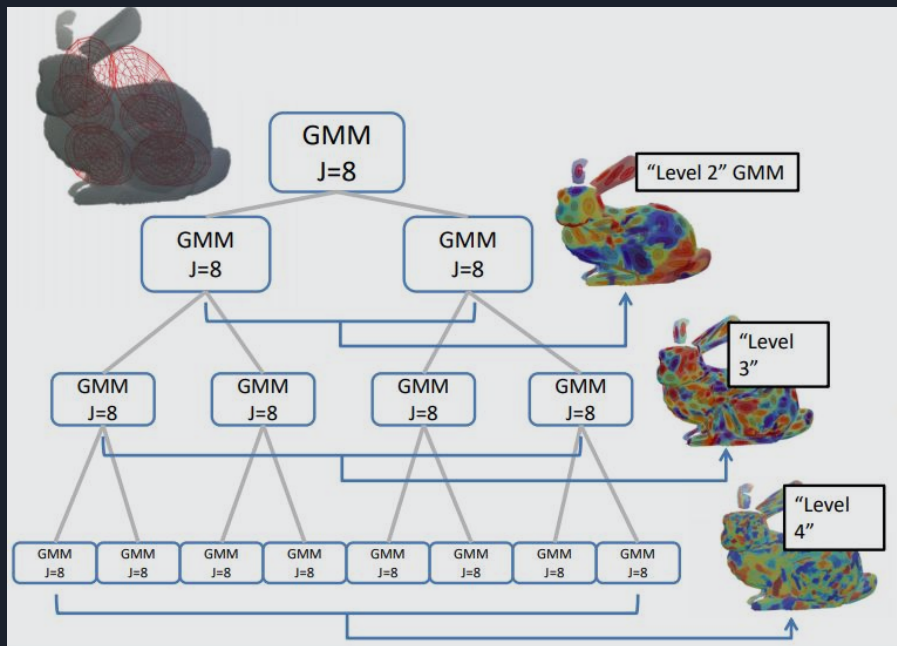


# GMM and Sparsity

Points in red region unlikely to be clustered with points in yellow region but GMM searches the whole space!



# Hierarchical Gaussian Mixture Models

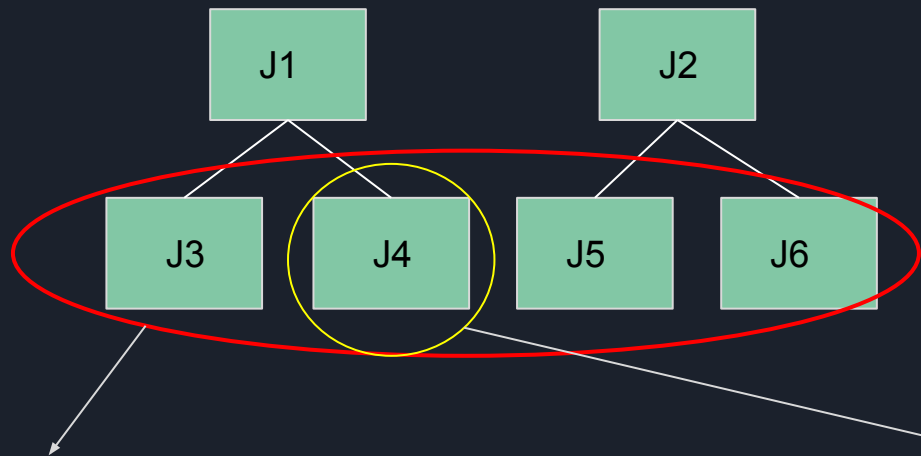


Source: [Nvidia - GPU Accelerated 3D Point Clouds](#)

- Conventional GMM evaluates ALL the components for EVERY point
- Hierarchical GMM's limits the search space to logarithmic by leveraging Octree-like division of points in clusters



# HGMM in CUDA



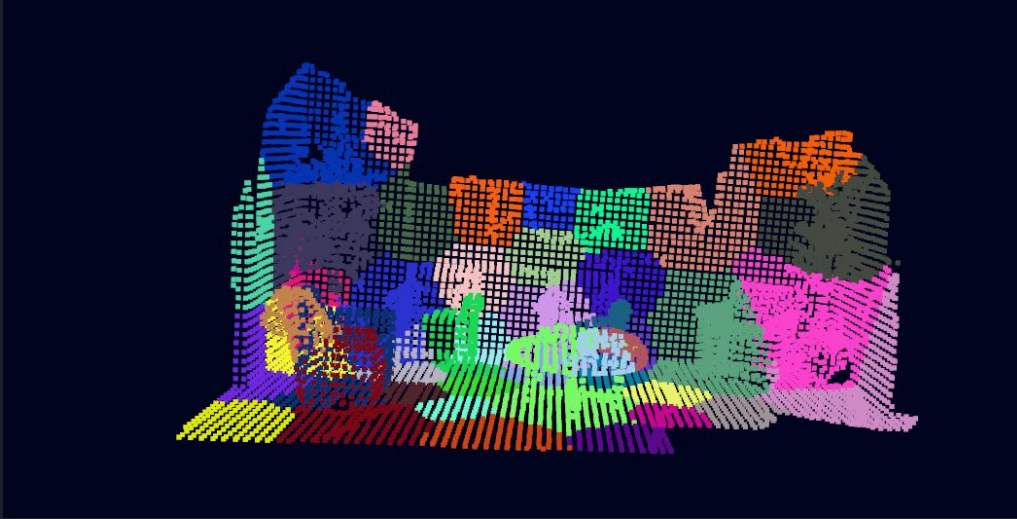
Parallelism per level across points

Accumulate moments per cluster  
per level with CUDA Atomic Add

# Use Cases



# Unsupervised Segmentation



- Good starting point for segmentation when ground truth is unavailable
- Lounge segmented into 10 clusters with all points of a furniture grouped together

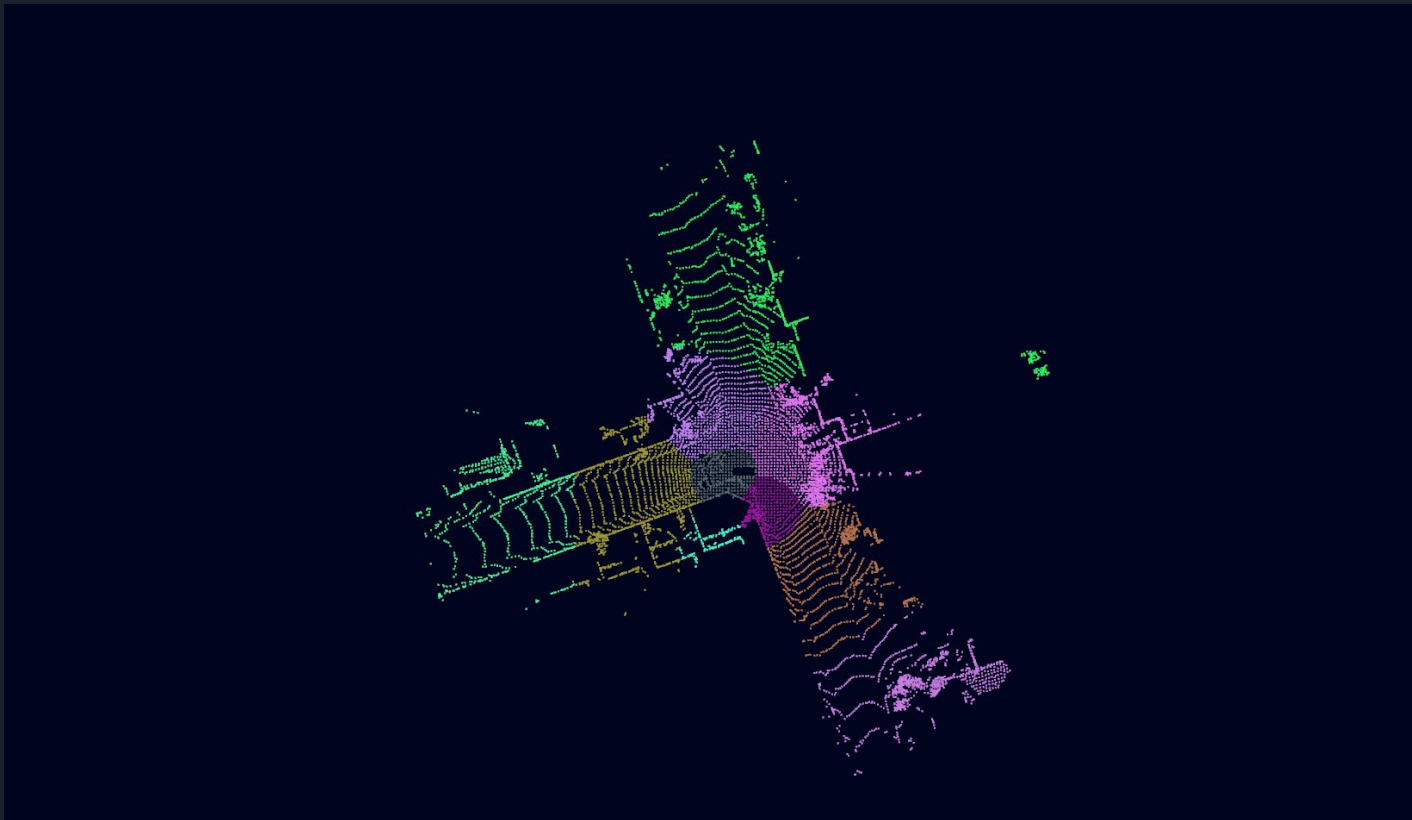


# Waymo Open Dataset

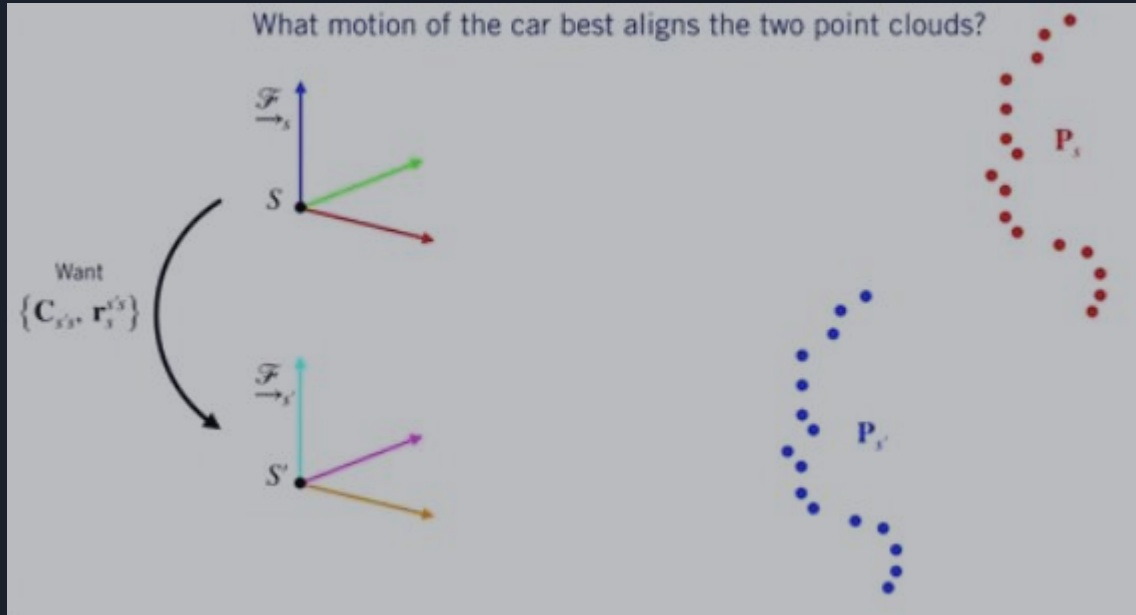
- 1) 1,000 segments of 20s each, collected at 10Hz (200,000 frames) in diverse geographies and conditions
- 2) Sensor data -
  - 1 mid-range lidar 4 short-range lidars 5 cameras (front and sides)
  - Synchronized lidar and camera data
  - Lidar to camera projections
  - Sensor calibrations and vehicle poses

Source - [Waymo Open Dataset](#)

# GMM on a stream of LIDAR Point Clouds



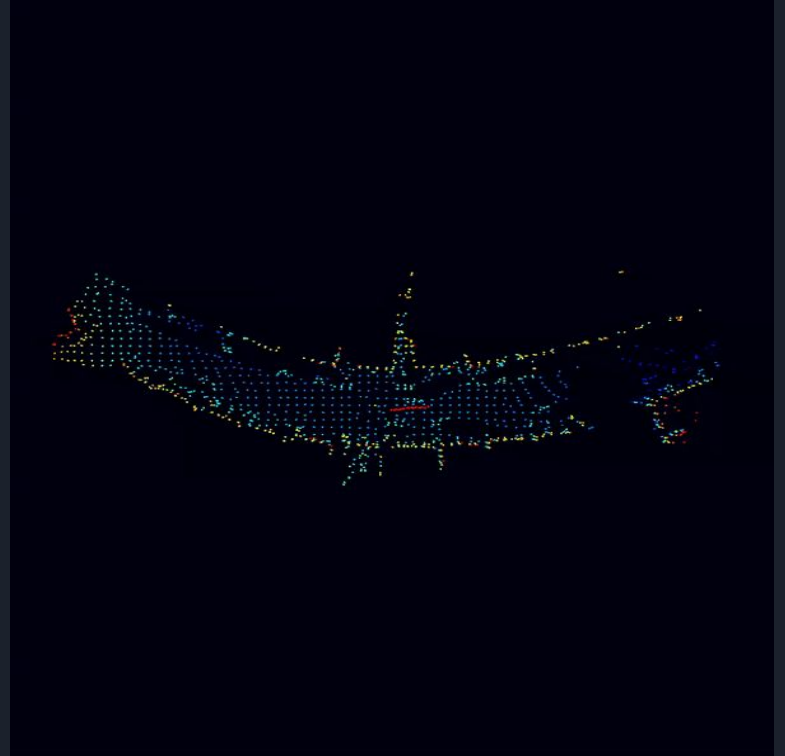
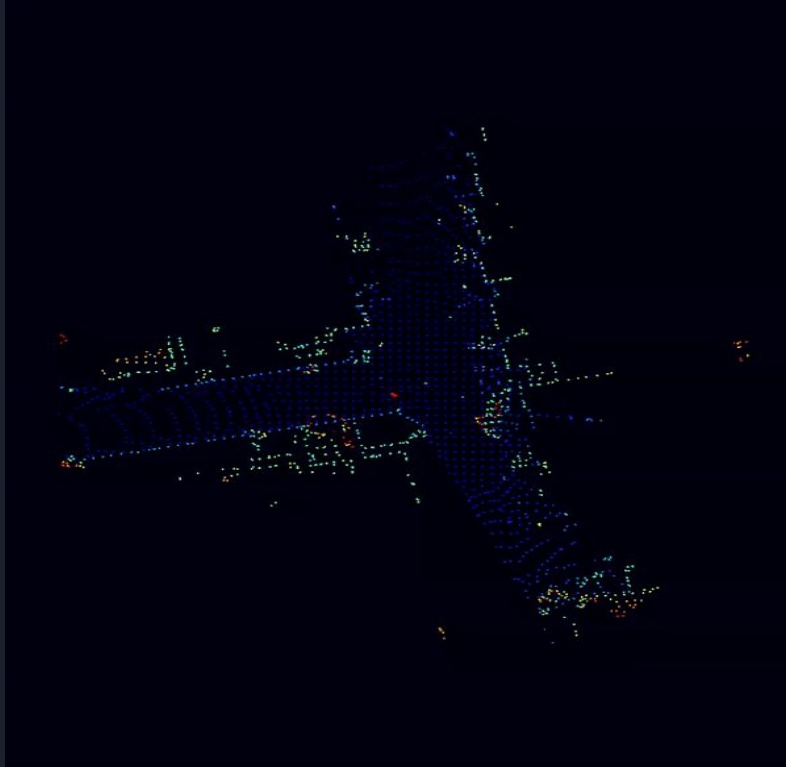
# Localization with PCR



Source - [State-Estimation and Localization for Self-Driving Cars](#)



# Localization with PCR



# Implementation and Performance Analysis





# CuPy and Numba

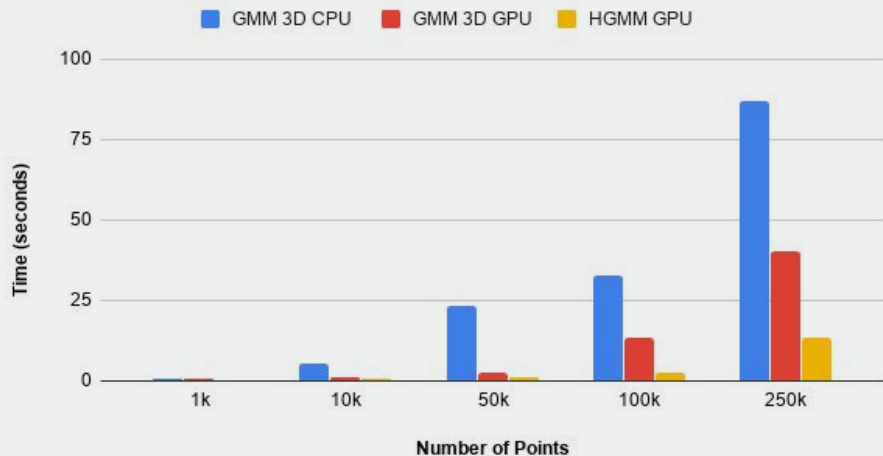
- CuPy - numpy arrays on the GPU. NumPy API but computations accelerated with the GPU
- Numba - write CUDA kernels in Python (JIT compiled to CUDA-C code)

```
from numba import cuda
@cuda.jit
def increment_by_one(an_array):
    # Thread id in a 1D block
    tx = cuda.threadIdx.x
    ty = cuda.blockIdx.x
    bw = cuda.blockDim.x

    idx = tx + ty * bw
    if idx < an_array.size:
        an_array[idx] += 1
```

# Performance Analysis

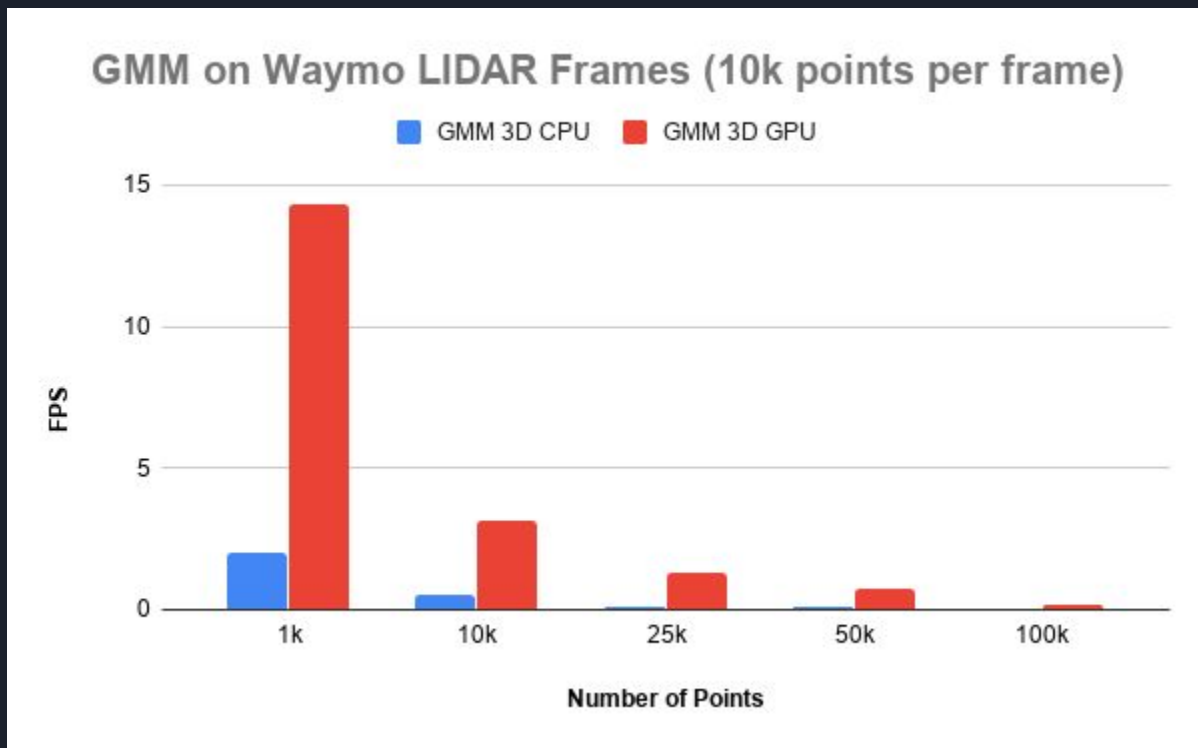
## GMM 3D Point Clouds (100 Components)



## Hierarchical GMM - Tree Levels ( $J = 8^d$ )



# Performance Analysis

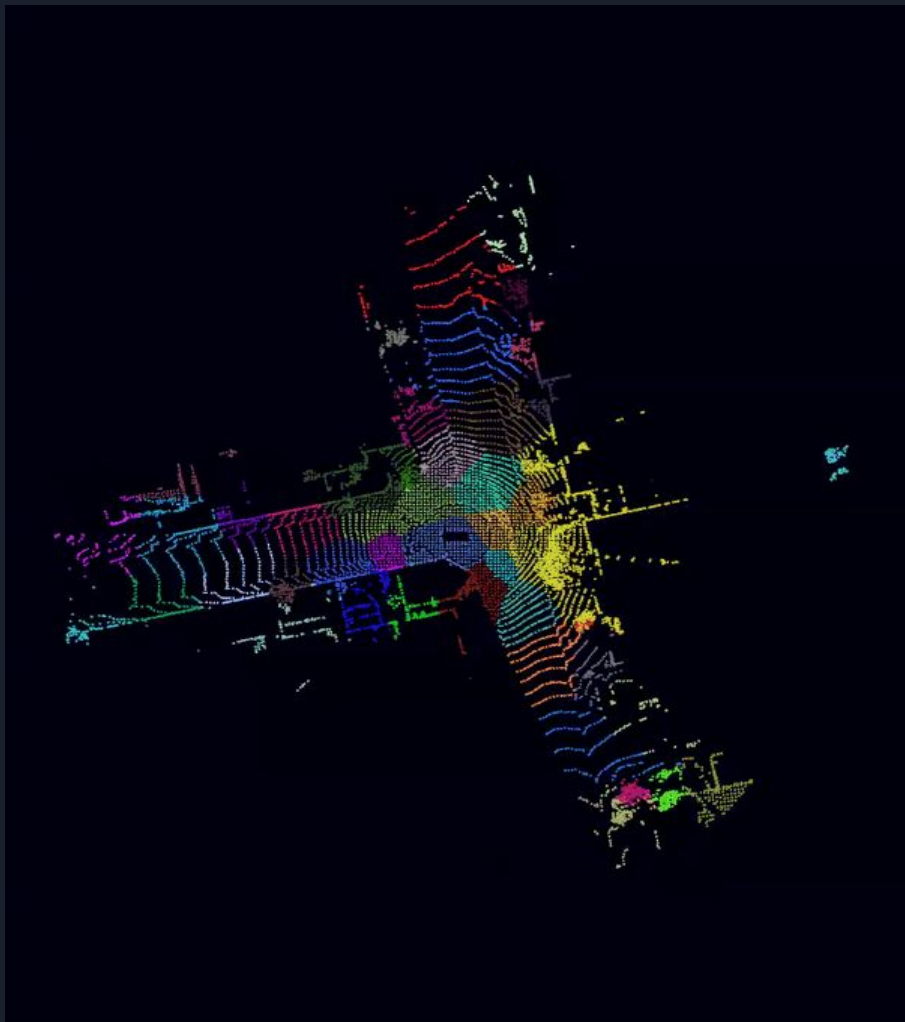




# Conclusion

- GMMs (CPU and GPU) on different 3D point cloud datasets
- Point Cloud Registration using GMM
- Hierarchical GMMs (CPU and GPU) for scaling to large point clouds
- GMMs on LIDAR point clouds from Waymo Open Dataset
- Localization with LIDAR point clouds using PCR





Waymo Open Dataset  
~120K Points  
110 FPS