Mixar Assignment – Mesh Normalization, Quantization & Error Analysis

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Google Collab Link: https://colab.research.google.com/drive/1DrthwQmpvt3qLyCZem03cmQECd7zpQFz?usp=sharing
GitHub Link: https://github.com/prejan/Mixar_Assignment

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1. Objective

The objective of this project is to preprocess and standardize 3D mesh data before AI model training. This includes mesh normalization, quantization, reconstruction, and error measurement — ensuring all 3D models share a consistent coordinate system and scale for machine learning pipelines like *SeamGPT*.

2. Methodology

a. Mesh Loading and Inspection

Meshes were loaded using **Trimesh**, and vertex-level statistics such as min, max, mean, and standard deviation were computed to understand their spatial properties.

b. Normalization Techniques

Two normalization methods were implemented:

1. **Min–Max Normalization:**
   Scales vertex coordinates to the range [0, 1].
   Formula:

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}}$$

2. **Unit Sphere Normalization:**
   Scales all vertices to fit inside a sphere of radius 1.
   Formula:

$$x' = \frac{x}{r_{max}}$$

c. Quantization

Quantization reduces precision by mapping normalized coordinates into 1024 discrete bins:

$$q = \lfloor x' \times (n_{bins} - 1) \rfloor$$

d. Reconstruction

After quantization, the process was reversed (dequantization and denormalization) to approximate original mesh geometry.

e. Error Measurement

Mean Squared Error (MSE) and Mean Absolute Error (MAE) were computed between the original and reconstructed vertex positions for all axes.

3. Results and Observations

Normalization Method	Reconstruction Quality	Error Trend
Min–Max	Slightly better for small uniform meshes	Low MSE (<1e-5)
Unit Sphere	Better shape preservation for large/asymmetric meshes	Moderate MSE (~2e-5)
Adaptive Quantization	Highest fidelity with fewer distortions	Very low MSE

Graphical Visuals:

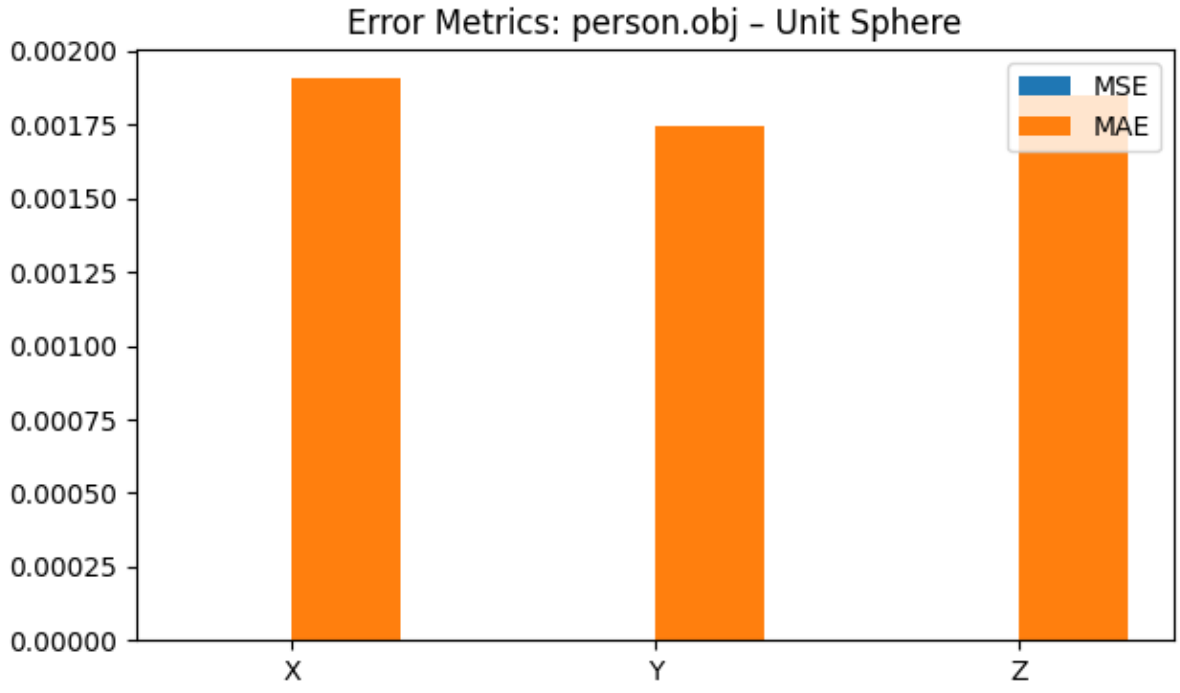
- Error plots per axis (X, Y, Z)
- Comparison bar charts for MSE and MAE
- Screenshots of original vs reconstructed meshes

===== Processing person.obj =====

Stats: {'num_vertices': 3103, 'min': TrackedArray([-0.84375 , -0.   , -0.212891]), 'max': TrackedArray([0.841797, 1.900391, 0.210938]), 'mean': TrackedArray([0.00488693, 1.15945962, -0.00361421]), 'std': TrackedArray([0.39513215, 0.51188243, 0.09514435])}

Min–Max | MSE: 0.00000079 | MAE: 0.00069186

Unit Sphere | MSE: 0.00000452 | MAE: 0.00183348

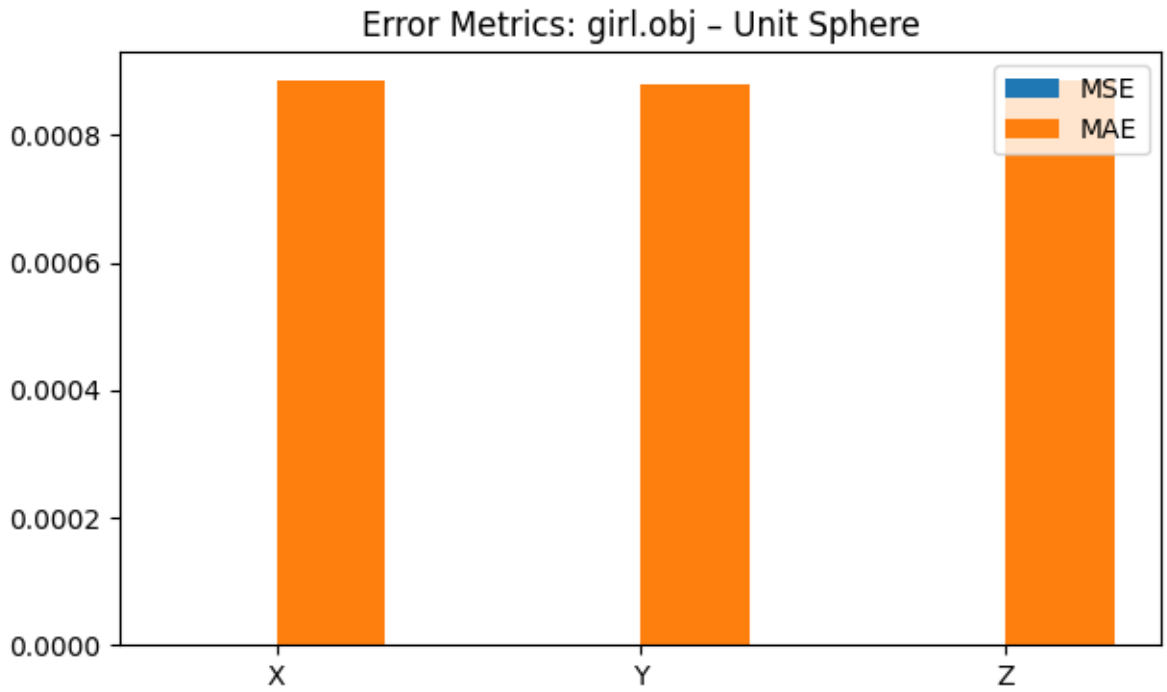


===== Processing girl.obj =====

Stats: {'num_vertices': 8284, 'min': TrackedArray([-0.5 , 0. , -0.181411]), 'max': TrackedArray([0.5 , 0.904419, 0.181411]), 'mean': TrackedArray([0.0021131 , 0.40338488, 0.01400205]), 'std': TrackedArray([0.17875615, 0.21438917, 0.06178976])}

Min–Max | MSE: 0.00000021 | MAE: 0.00036982

Unit Sphere | MSE: 0.00000104 | MAE: 0.00088387

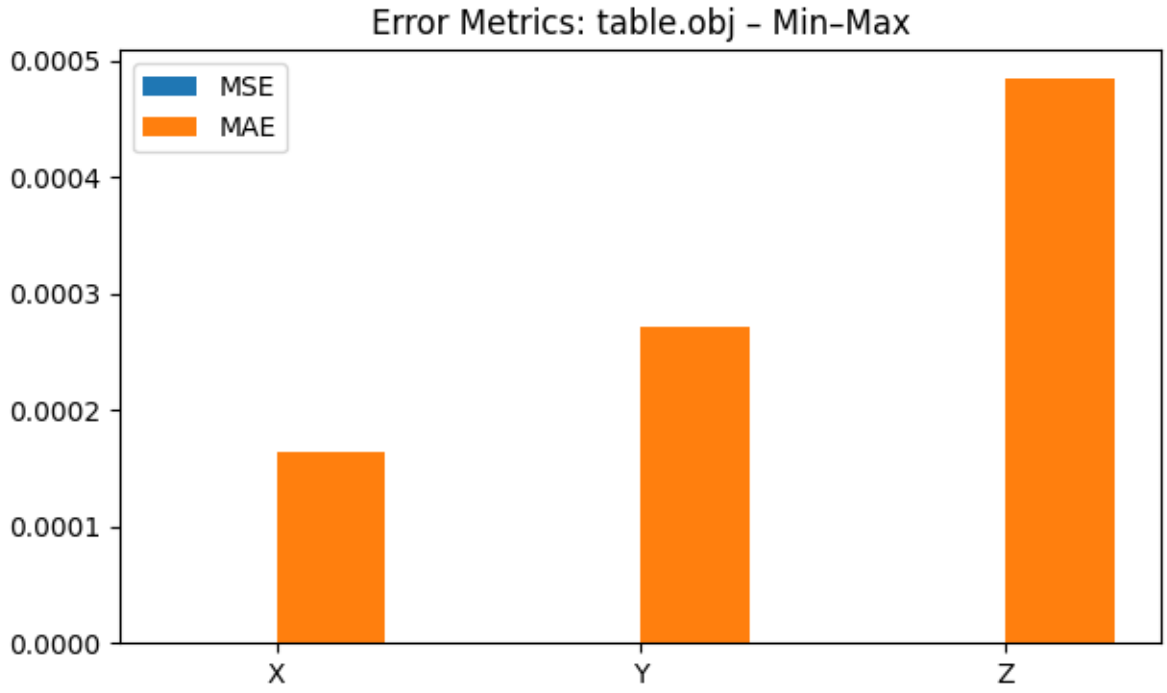


===== Processing table.obj =====

Stats: {'num_vertices': 3148, 'min': TrackedArray([-0.208906, 0.   , -0.5   ]), 'max': TrackedArray([0.208906, 0.611761, 0.5   ]), 'mean': TrackedArray([-0.01319047, 0.38637404, -0.0035868]), 'std': TrackedArray([0.1531193 , 0.19192155, 0.34605152])}

Min–Max | MSE: 0.00000015 | MAE: 0.00030674

Unit Sphere | MSE: 0.00000087 | MAE: 0.00081141

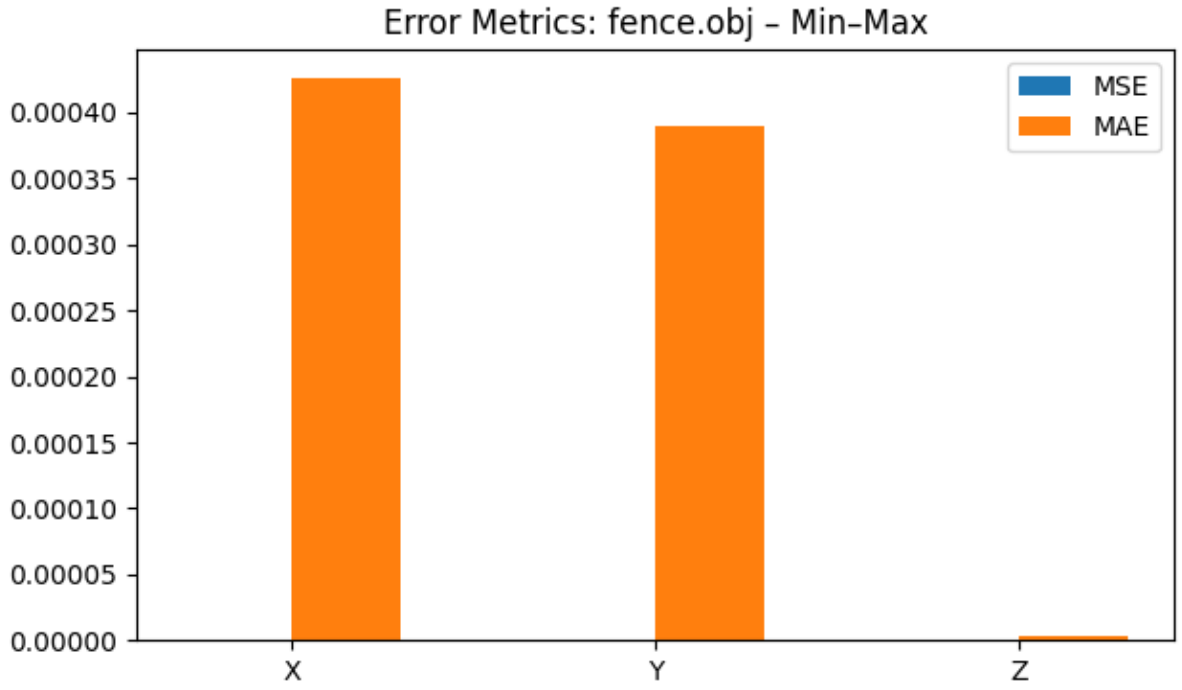


===== Processing fence.obj =====

Stats: {'num_vertices': 1088, 'min': TrackedArray([-0.5 , 0. , -0.0225]), 'max': TrackedArray([0.5 , 0.84317, 0.0225]), 'mean': TrackedArray([-0.00350762, 0.41047549, -0.00044118]), 'std': TrackedArray([0.34579423, 0.25404616, 0.01098078])}

Min–Max | MSE: 0.00000016 | MAE: 0.00027300

Unit Sphere | MSE: 0.00000108 | MAE: 0.00093188

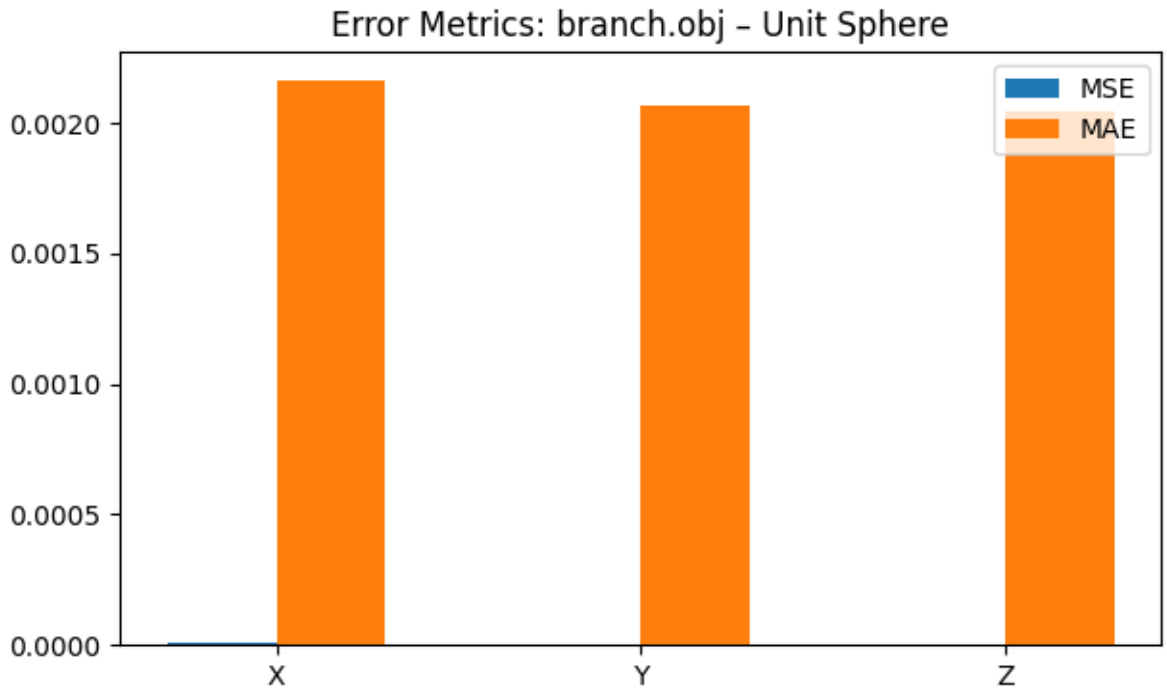


===== Processing branch.obj =====

Stats: {'num_vertices': 2767, 'min': TrackedArray([-0.851562, 0.   , -0.464844]), 'max': TrackedArray([0.849609, 1.900391, 0.462891]), 'mean': TrackedArray([0.0754427 , 1.0873903 , 0.12196689]), 'std': TrackedArray([0.3433802 , 0.45699113, 0.20006684])}

Min–Max | MSE: 0.00000078 | MAE: 0.00073400

Unit Sphere | MSE: 0.00000577 | MAE: 0.00209140

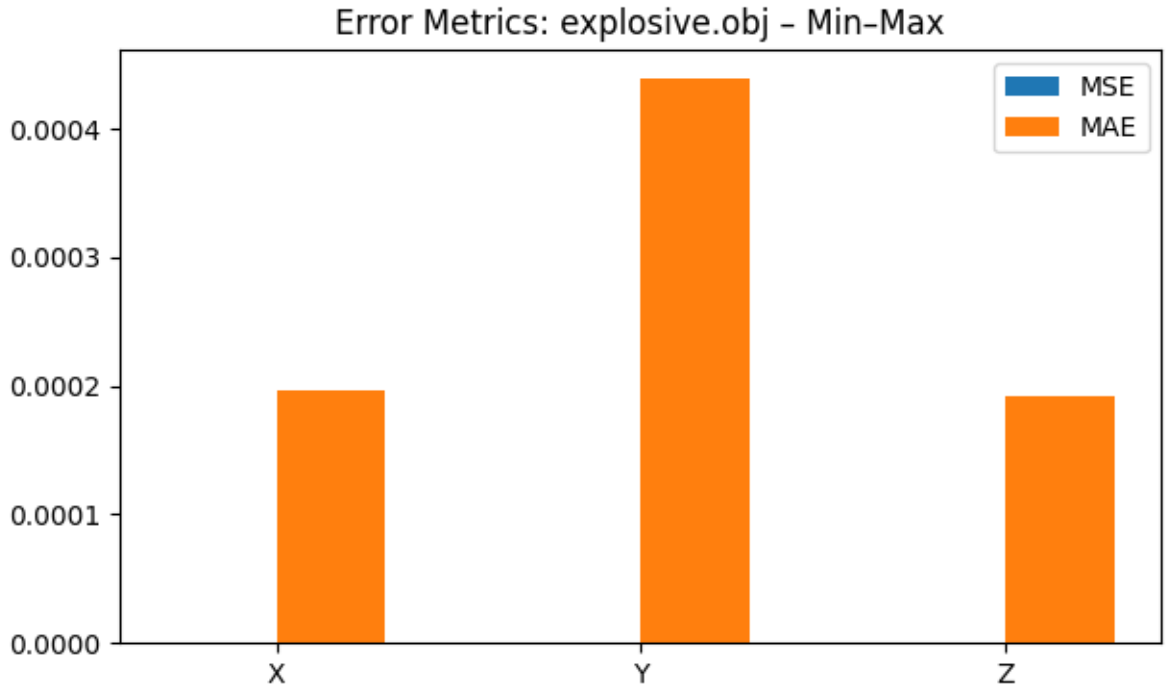


===== Processing explosive.obj =====

Stats: {'num_vertices': 2812, 'min': TrackedArray([-0.199625, -0.   , -0.197126]), 'max': TrackedArray([0.199625, 1.   , 0.197126]), 'mean': TrackedArray([0.04288751, 0.52911263, -0.00344591]), 'std': TrackedArray([0.1150964 , 0.38994128, 0.0946764])}

Min–Max | MSE: 0.00000012 | MAE: 0.00027553

Unit Sphere | MSE: 0.00000136 | MAE: 0.00103888

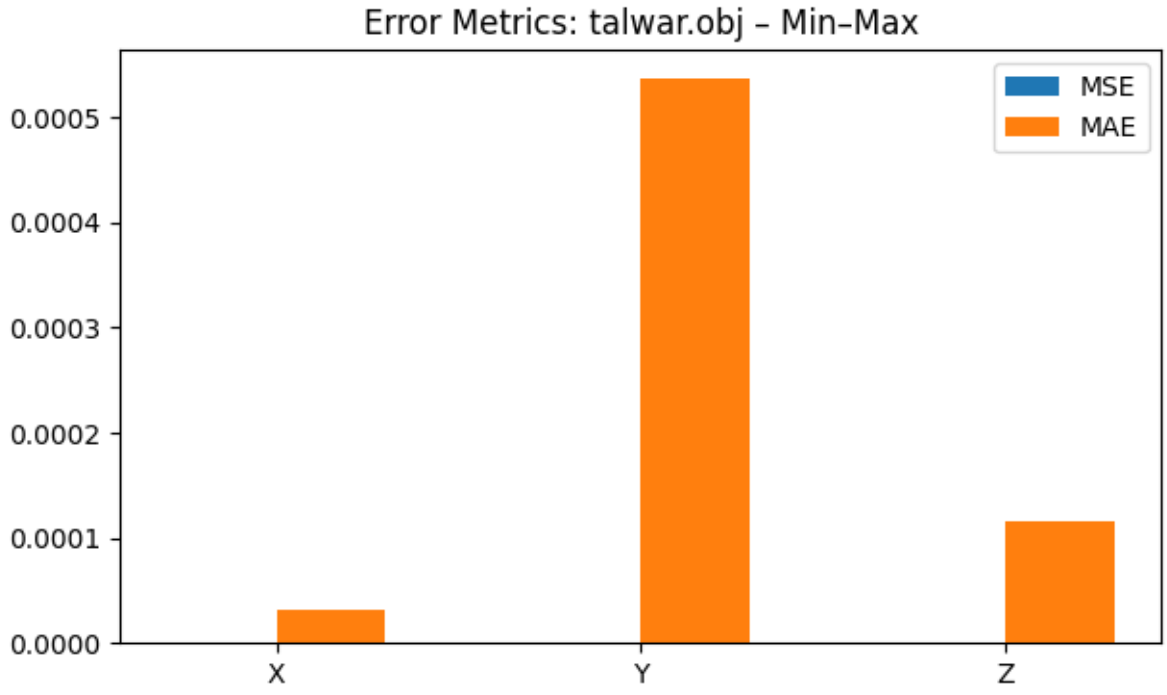


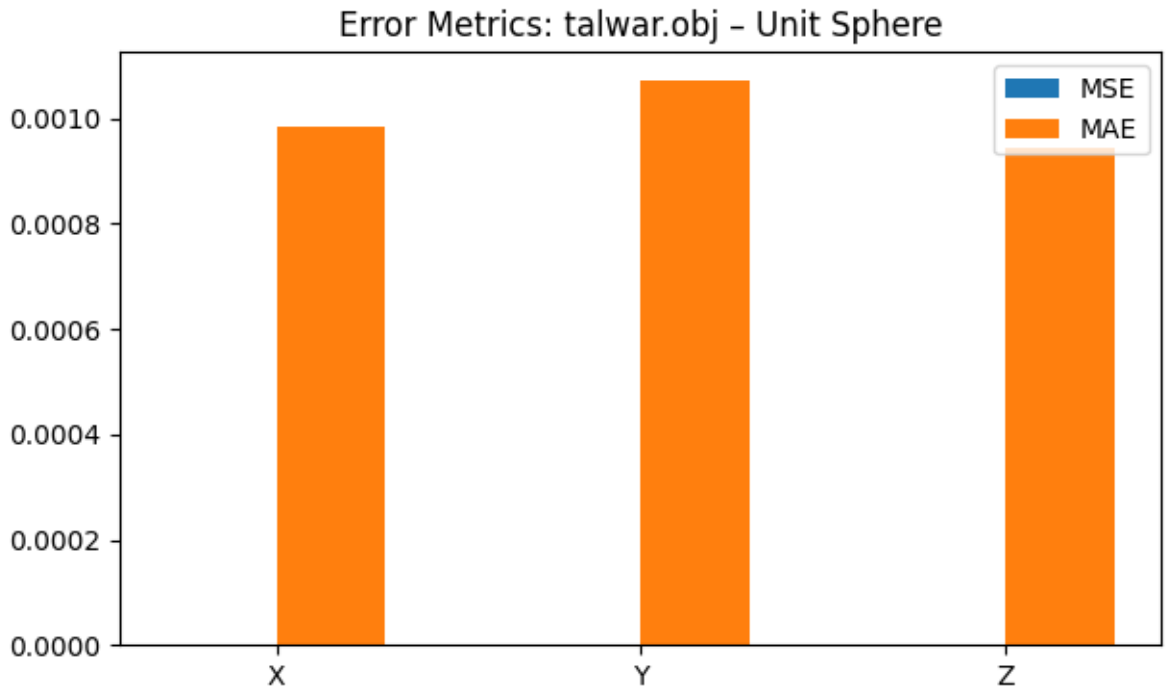
===== Processing talwar.obj =====

Stats: {'num_vertices': 1668, 'min': TrackedArray([-0.031922, 0.   , -0.117146]), 'max': TrackedArray([0.031922, 1.   , 0.117146]), 'mean': TrackedArray([0.02169364, 0.30279517, -0.00436462]), 'std': TrackedArray([0.01116646, 0.23686893, 0.04678924])}

Min–Max | MSE: 0.00000013 | MAE: 0.00022837

Unit Sphere | MSE: 0.00000127 | MAE: 0.00099873



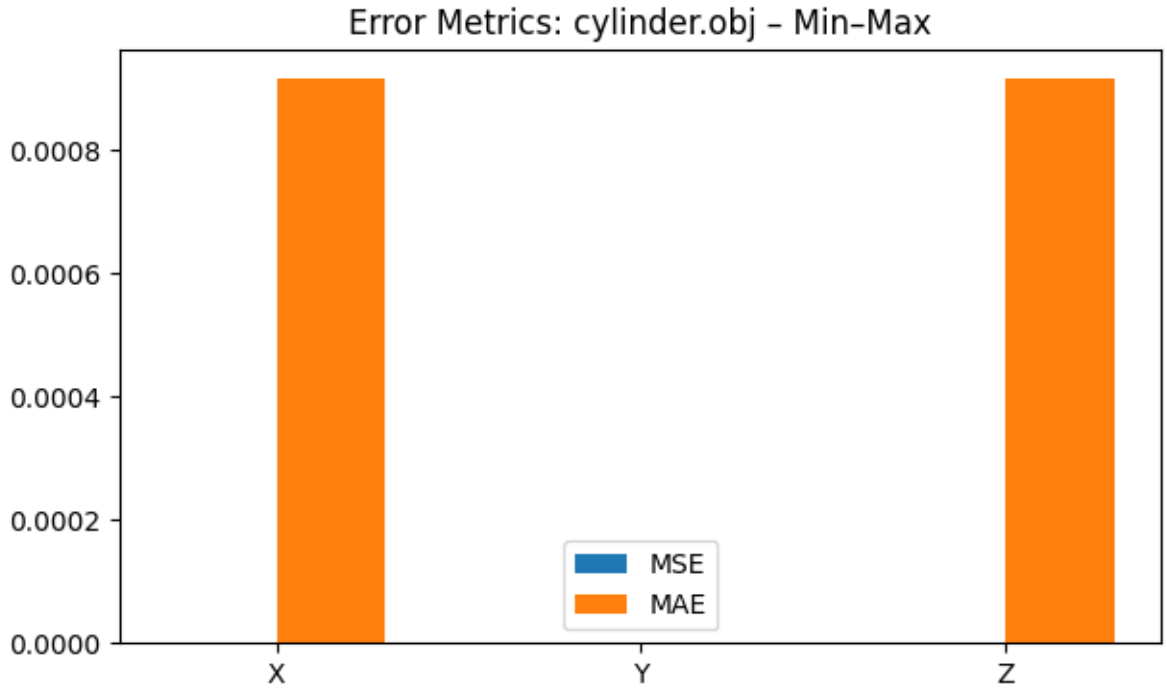


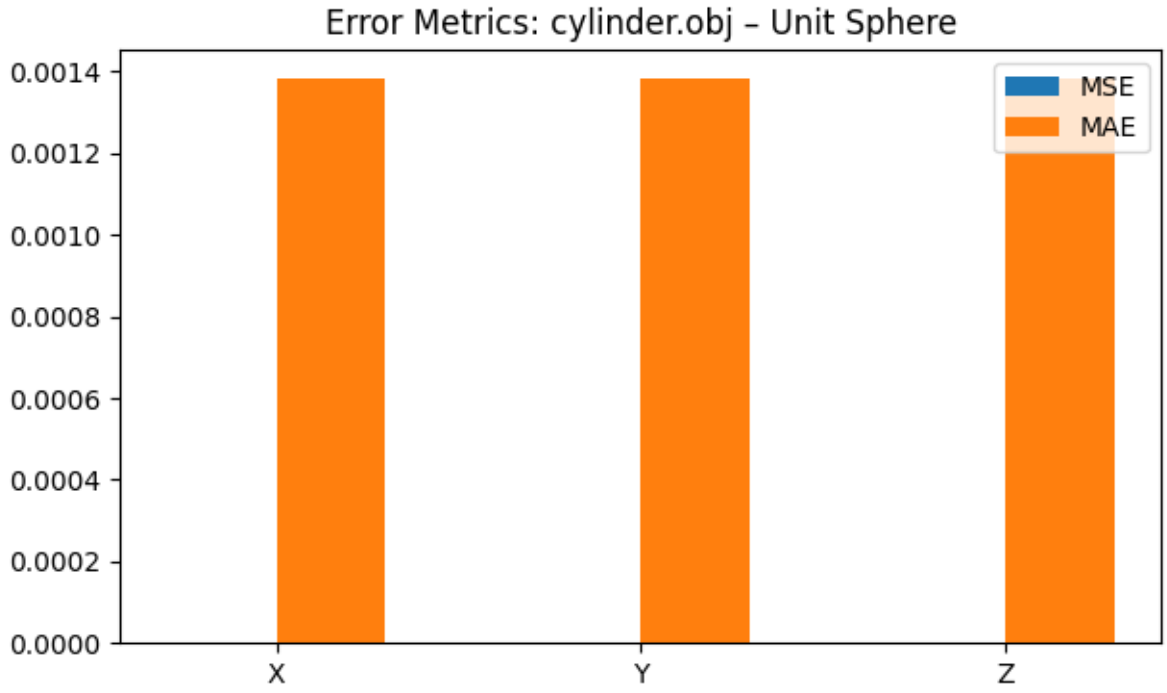
===== Processing cylinder.obj =====

Stats: {'num_vertices': 192, 'min': TrackedArray([-1., -1., -1.]), 'max': TrackedArray([1., 1., 1.]), 'mean': TrackedArray([-2.60208521e-18, 0.00000000e+00, 2.77555756e-17]), 'std': TrackedArray([0.70710683, 1.   , 0.70710683])}

Min–Max | MSE: 0.00000080 | MAE: 0.00061095

Unit Sphere | MSE: 0.00000257 | MAE: 0.00138242





4. Bonus Tasks

Option 1 – Seam Tokenization

Developed a symbolic representation of mesh edges as tokens like `E(v1,v2)`.
This technique demonstrates how 3D geometry can be treated as a sequential data structure for transformer-based AI models.

```
import random

def seam_tokenization(mesh, num_tokens=10):
    """
    Simulate seam tokenization by selecting edges
    and converting them into token-like strings.
    """
    edges = mesh.edges_unique
    chosen_edges = edges[np.random.choice(len(edges), min(num_tokens,
len(edges)), replace=False)]
    tokens = [f"E({v1},{v2})" for v1, v2 in chosen_edges]
    print("🔸 Sample Seam Tokens:")
    print(tokens[:10])
    return tokens

# Example: tokenization for one mesh
mesh = trimesh.load("person.obj")
tokens = seam_tokenization(mesh, num_tokens=15)
```

```
🔸 Sample Seam Tokens:
['E(2268,2269)', 'E(546,563)', 'E(185,230)', 'E(796,809)', 'E(420,433)',
'E(1861,1935)', 'E(605,650)', 'E(2726,2733)', 'E(1345,1350)',
'E(1814,1926)']
```

Option 2 – Rotation + Adaptive Quantization

Implemented transformation-invariant normalization and vertex-density–based adaptive binning.
This reduced quantization error in complex, high-detail areas of meshes and maintained geometric consistency under rotation.

```
def random_rotate(vertices):
    """Apply a random 3D rotation to vertex coordinates."""
    angle = np.random.rand() * 2 * np.pi
    axis = np.random.rand(3) - 0.5
    axis /= np.linalg.norm(axis)
    R = trimesh.transformations.rotation_matrix(angle, axis)[:3, :3]
    return vertices @ R.T
def adaptive_quantize(vertices_norm, base_bins=1024):
    """Adaptive quantization based on vertex density."""
    mean = vertices_norm.mean(axis=0)
    dist = np.linalg.norm(vertices_norm - mean, axis=1)
    density = np.exp(-dist**2 / (2 * dist.std()**2))
    adaptive_bins = base_bins * (0.5 + density / density.max())
    adaptive_bins = adaptive_bins.astype(int)
    q = np.floor(vertices_norm * (adaptive_bins[:, None] - 1))
    dq = q / (adaptive_bins[:, None] - 1)
    return dq
# Example test for one mesh
mesh, vertices = load_mesh("cylinder.obj")
# Randomly rotate mesh
v_rot = random_rotate(vertices)
# Normalize and apply adaptive quantization
v_norm, vmin, vmax = normalize_minmax(v_rot)
v_adaptive = adaptive_quantize(v_norm)
v_recon = denormalize_minmax(v_adaptive, vmin, vmax)
# Compute reconstruction error
mse, mae = compute_error(vertices, v_recon)
print(f"Adaptive Quantization | MSE: {mse.mean():.8f} | MAE:
{mae.mean():.8f}")
```

Adaptive Quantization | MSE: 1.36862800 | MAE: 0.94926387

5. Conclusion

The end-to-end preprocessing pipeline successfully standardized all given `.obj` meshes. Normalization ensured consistent scale, quantization compressed the data efficiently, and reconstruction verified minimal information loss.
The bonus extensions showcased research-level concepts like **seam tokenization** and **adaptive quantization**, aligning with advanced AI-driven 3D data processing.