CSIRO

Australia's National Science Agency

# MongeNet : Efficient Sampler for Geometric Deep Learning

Leo Lebrat†, Rodrigo Santa Cruz†, Clinton Fookes, and Olivier Salvado.

†equal contribution

THE AUSTRALIAN E-HEALTH RESEARCH CENTRE

QUT Queensland University of Technology

maxwellplus+

# Measuring distance between triangle meshes

**Sampling** points on surfaces is a cornerstone element of **Geometrical Deep Learning**

- **Fast** and **balanced** metric during training (Sampling + Chamfer).
- **Steady** and **reliable** evaluation during testing (Sampling + EMD + Chamfer Normal).

However, current sampling method is based on **random uniform sampling**

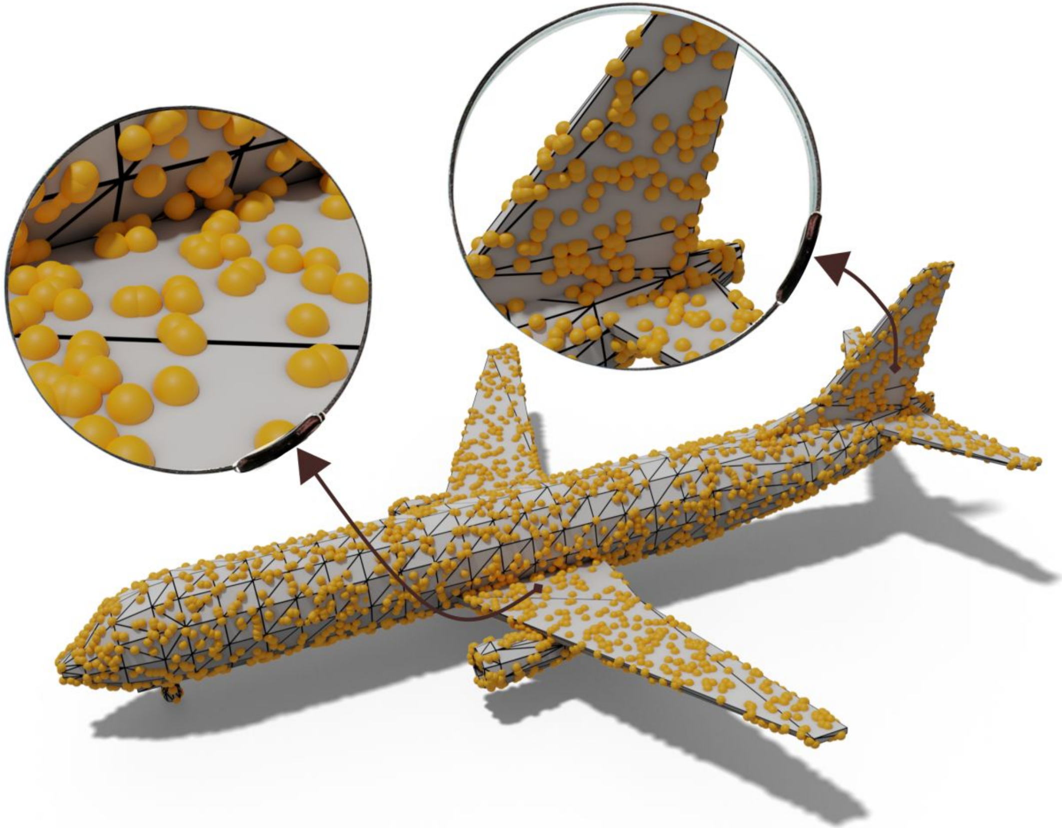
Given the triangle $T = (V^1, V^2, V^3)$ the point $p$ is sampled

$$p = (1 - \sqrt{u_1})V^1 + \sqrt{u_1}u_2V^2 + (1 - u_2)\sqrt{u_1}V^3,$$

with $u_1, u_2 \sim U([0, 1])$

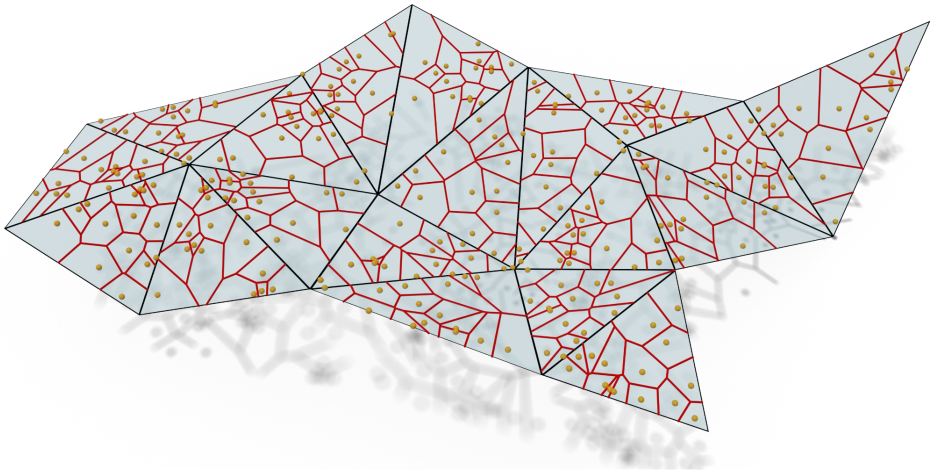
Points are sampled **independently** and are unevenly distributed.

# Undersampled Areas and Clamping

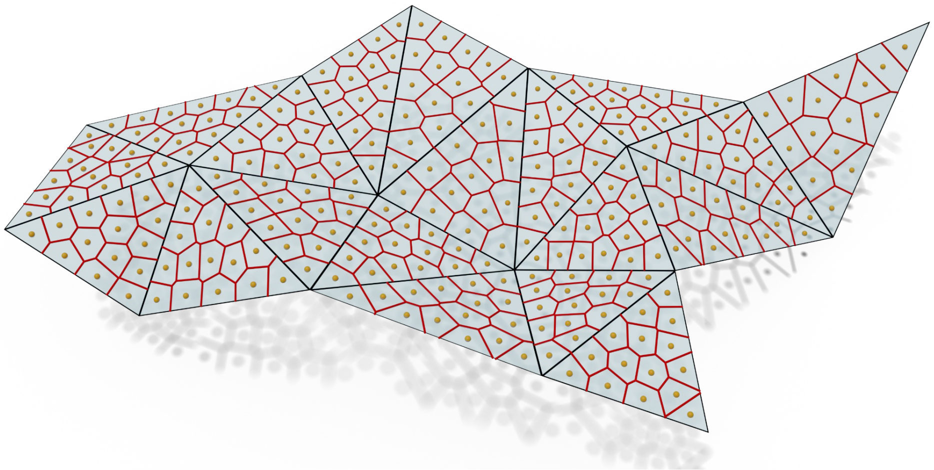


# Measuring distance between triangle meshes

In this paper we propose a sampler based on **Optimal Transport** (OT), that given a Dirac masses budget (point cloud) minimizes the OT-distance to the **triangle mesh**.



Classical Sampling



MongeNet Sampling

# Learn to sample

The sampling is learned in a supervised manner:

Given sampling $\mathbf{S}$ and $\ell$ sampled points, MongeNet $\mathbf{f}_\theta(t, \ell, p)$ minimizes:

$$\mathcal{L}(t, \ell, p, \mathbf{S}) = \underbrace{W_2^\varepsilon(\mathbf{f}_\theta(t, \ell, \mathbf{p}), \mathbf{S})}_{\text{fidelity}} - \alpha \underbrace{W_2^\varepsilon(\mathbf{f}_\theta(t, \ell, \mathbf{p}), \mathbf{f}_\theta(t, \ell, \mathbf{p}'))}_{\text{diversity}}$$

with $W_2^\varepsilon$ the $\varepsilon$-regularized optimal transport [Cuturi, 2013, Feydy et al., 2020] and $\mathbf{p}, \mathbf{p}' \sim \mathcal{N}(0, 1)$

- We uniformly **remap** all of the triangles to a unitary triangle (**scale**, **rotation** and **translation** invariant learning problem).
- We develop a online **edge-splitting** scheme to sample arbitrarily large number of points.
- We encourage **diversity** of the resulting sampling patterns.

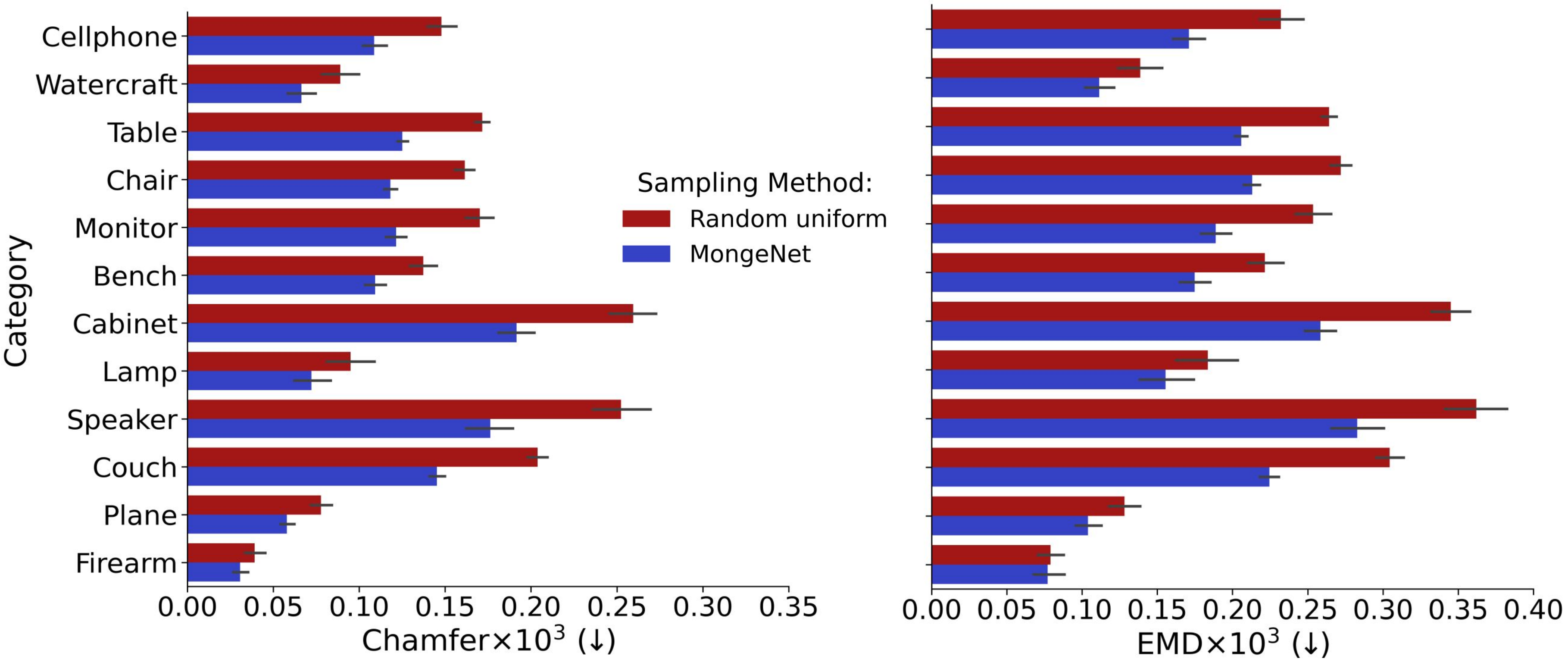
# Qualitative results

## 150K points : MongeNet = **evenly distributed** point-cloud

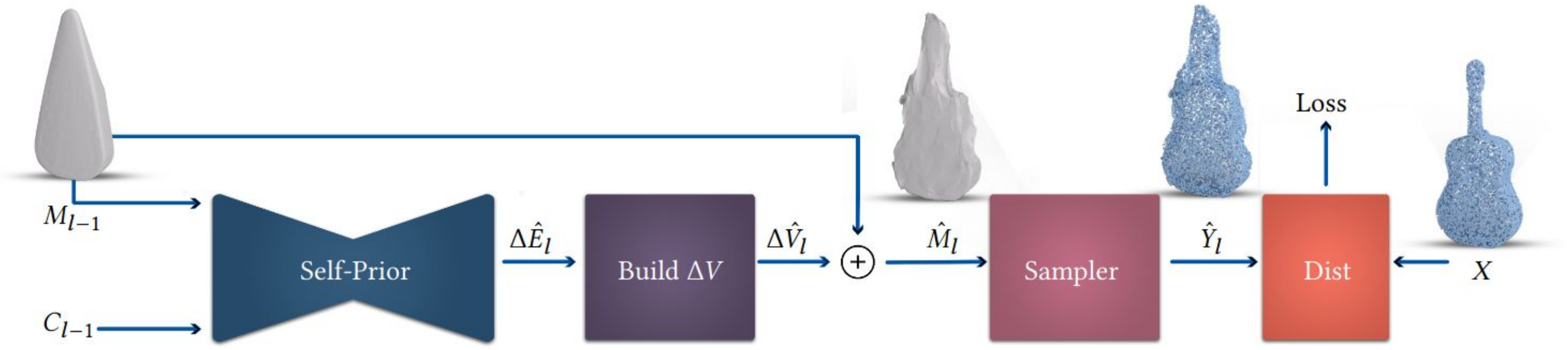
Template mesh | Uniform sampling | Mongenet

# Quantitative results

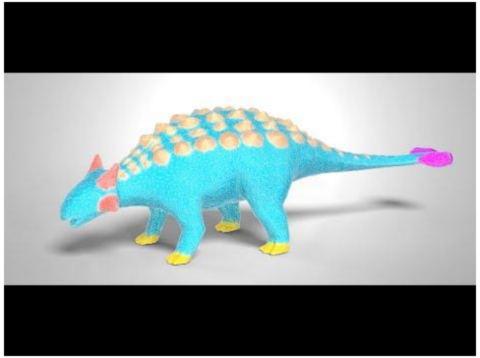
We measure the approximation error for 10k sampled points on the ShapeNet dataset.



# Mesh Approximation Application Using Point2Mesh

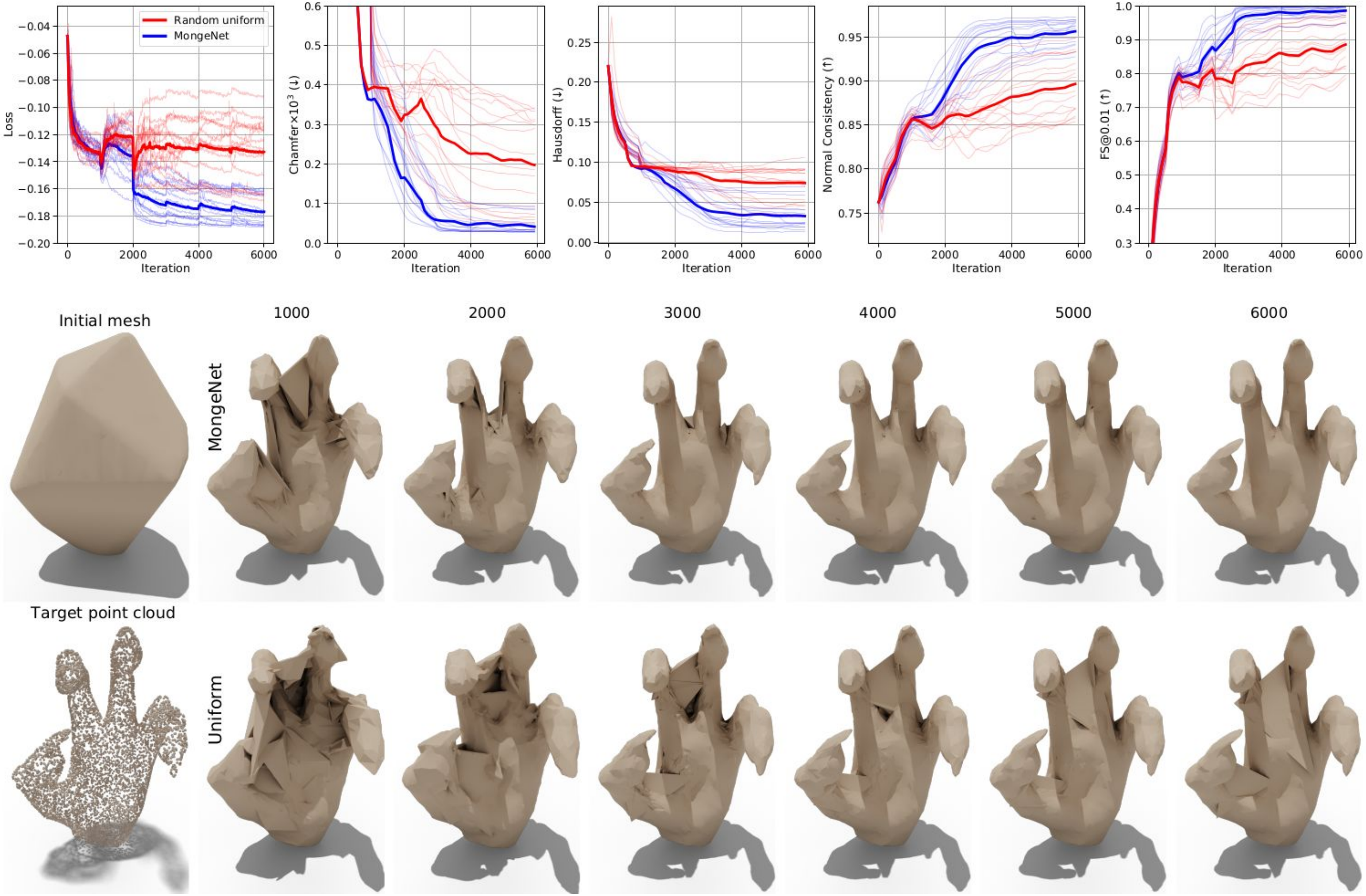



[Hanocka et al., *Point2Mesh,* SIGGRAPH 2020]



Random Uniform Sampling

MongeNet


Random uniform
MongeNet
Loss
Chamfer×10³ (↓)
Hausdorff (↓)
Normal Consistency (↑)
FS@0.01 (↑)
Iteration
Initial mesh
Target point cloud
1000
2000
3000
4000
5000
6000
MongeNet
Uniform

# Summary

- MongeNet is **fast** and involves a **limited overhead**.
- It can replace seamlessly **pytorch3D** sampling_points_from_mesh.
- A better sampling allows:
  - Training faster and better models.
  - Reducing the variance and the approximation error for evaluation.

Our code is freely available:

https://github.com/lebrat/MongeNet