



Zhe ZHANG  
Digital Art Lab



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# SJTU Summer Camp

School of Software Engineering  
Tongji University  
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Zhe ZHANG, 2020.07

# Neural Subdivision



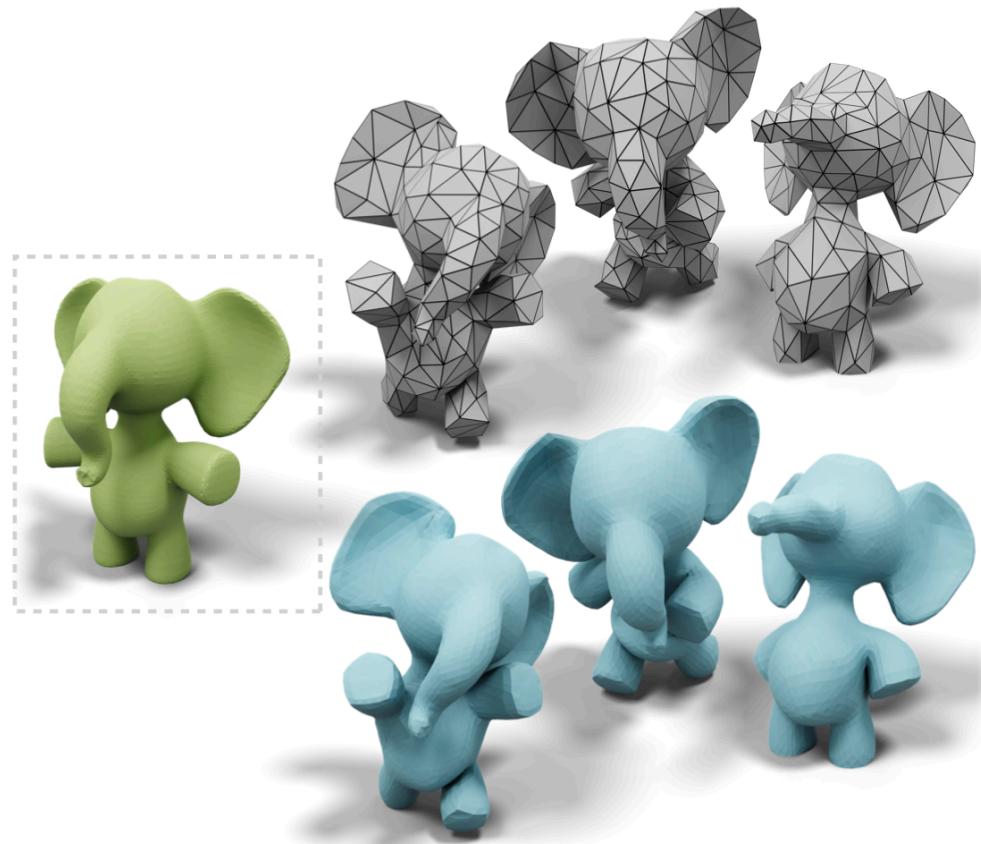
# Table of Content

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- Background
  - What is Subdivision?
  - What is Neural Subdivision?
  - Neural Geometry Learning
- Neural Subdivision
  - Overview
  - Training and Loss
  - Data Generation
  - Network Architecture
- Comparison
  - Evaluations
  - Limitations & Further Works



# What is Subdivision?

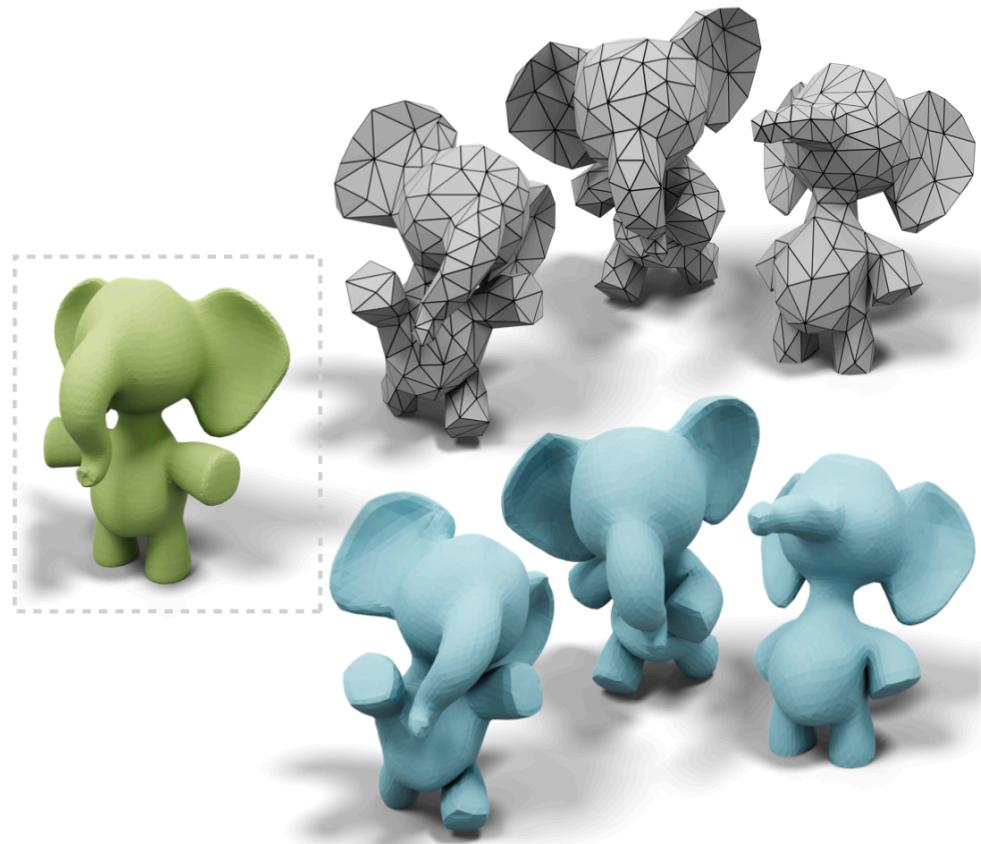


## 【Application】

- Interactive modeling
  - A modeler may start with a very coarse cage, adjust vertex positions, then subdivide once, adjust the finer mesh vertices, and repeat this process until satisfied
- Render for points of interest



# What is Subdivision?



## 【Classic Methods】

**Core idea:** recursive up-sampling of a discrete surface mesh

- **divide input mesh into vertices**
  - split edges
  - add vertices
- **linear weighted average:** smooth positions of the mesh vertices



# What is Subdivision?

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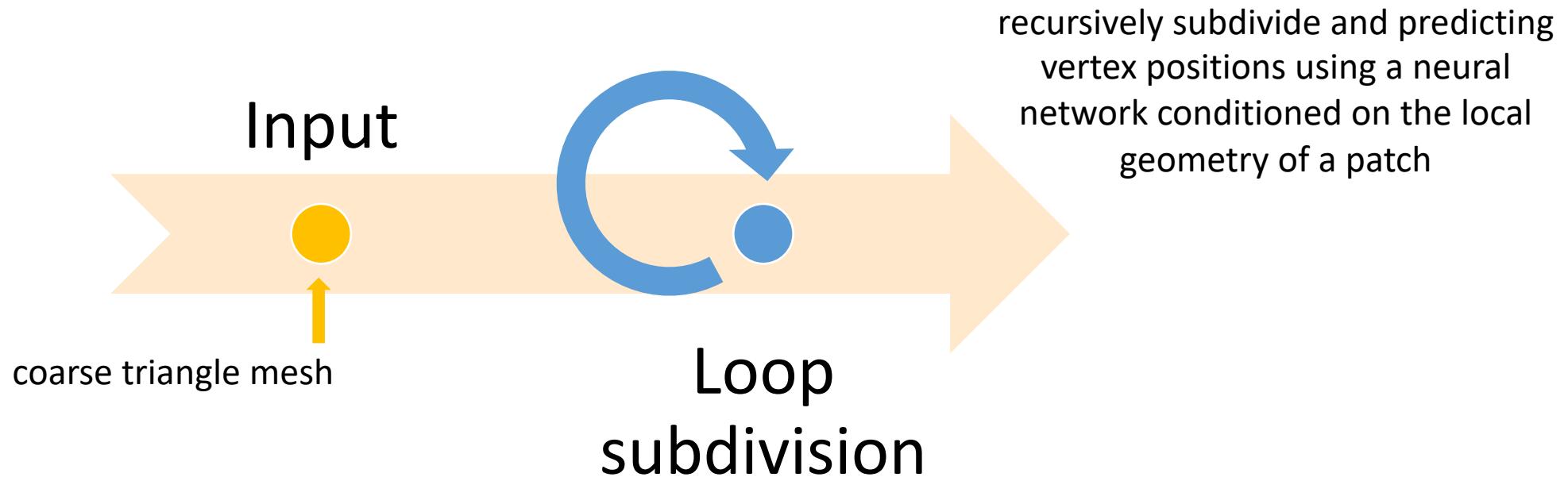
## 【Weakness】

- Usually overly smooth the entire shape
- Details loss
- Fixed on-size-fits-all weighting rules globally(Unuse lots of information)



# What is Neural Subdivision?

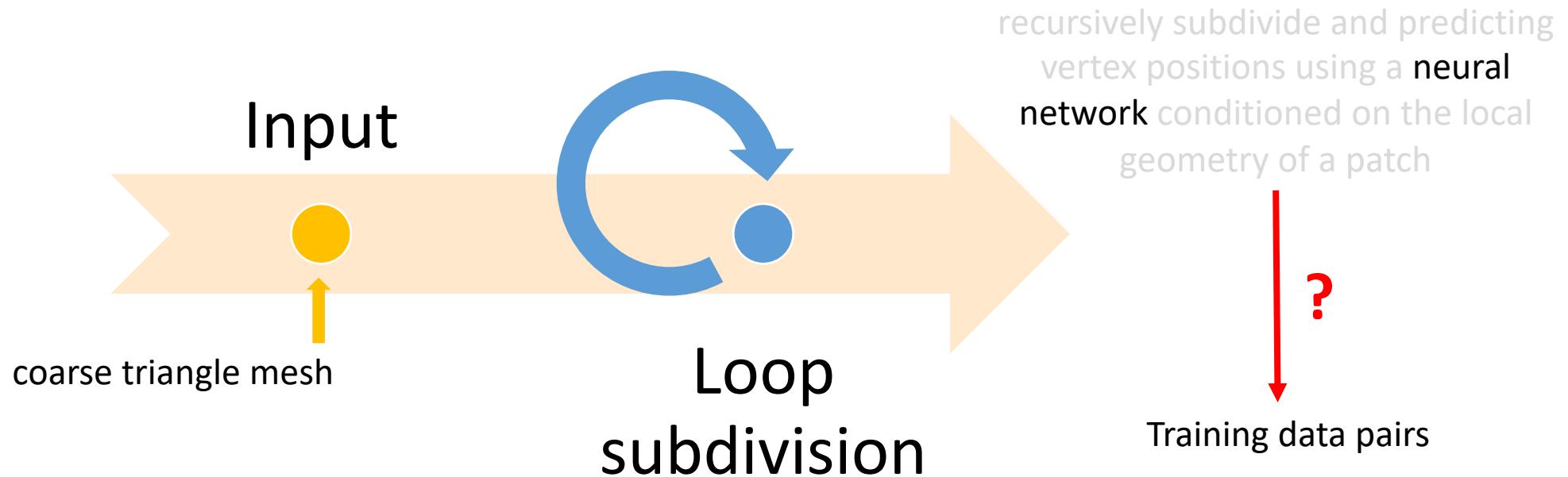
A novel framework for data-driven coarse-to-fine geometry modeling.





# What is Neural Subdivision?

A novel framework for data-driven coarse-to-fine geometry modeling.

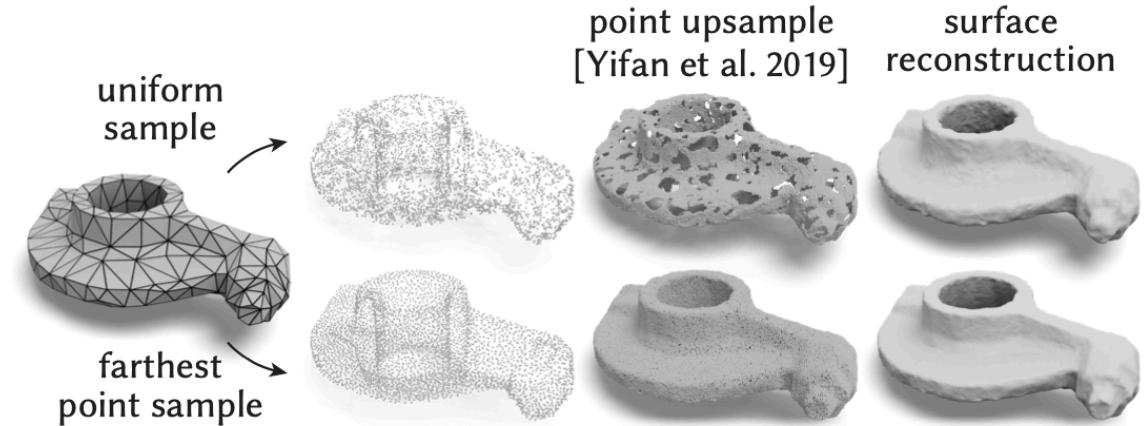




# Neural Geometry Learning

## 【Deep point cloud upsampling】

- lack connectivity information
- require the neural network to estimate the structure of the underlying manifold
- post process is often required to convert the output of point-based methods to meshes(not end-to-end trainable system)



## 【Others】

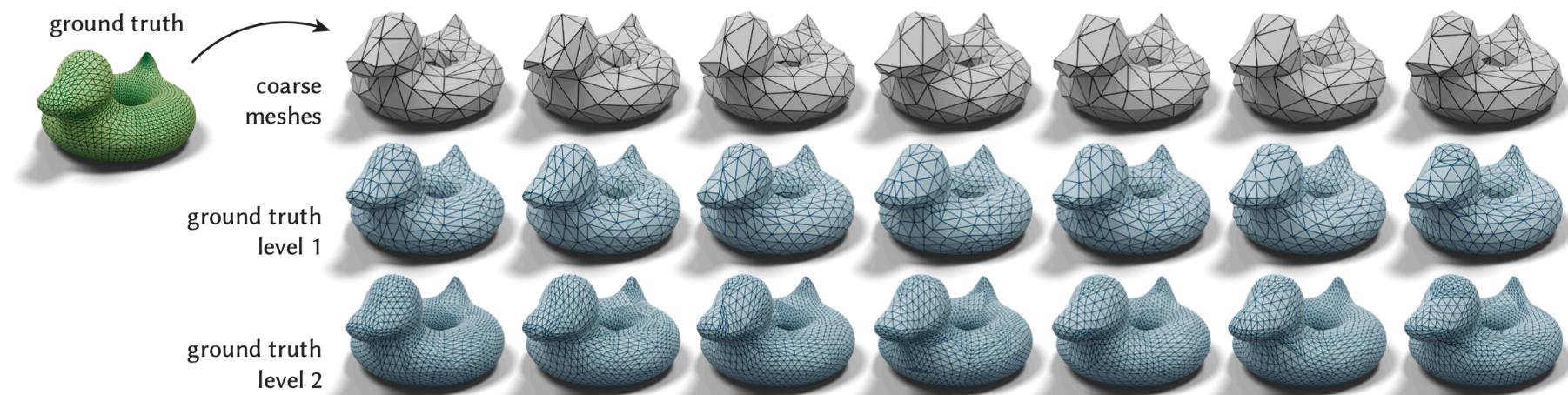
- deform global template
- using a local or global parameterization to unfold a mesh into 2D grid
- apply graph-based techniques adapted for mesh



# Neural Geometry Learning

## 【Paper Approach】

Randomly generate low-resolution versions of training samples while maintaining bijection between their surfaces.





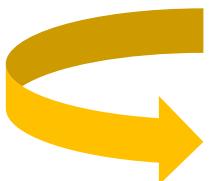
# Neural Geometry Learning

## 【Paper Approach】

Randomly generate low-resolution versions of training samples while maintaining bijection between their surfaces.

## 【MeshCNN】

Deterministic tasks -> learn filter over the local mesh structure via undirected edges



Generative tasks -> develop features over the half-flaps



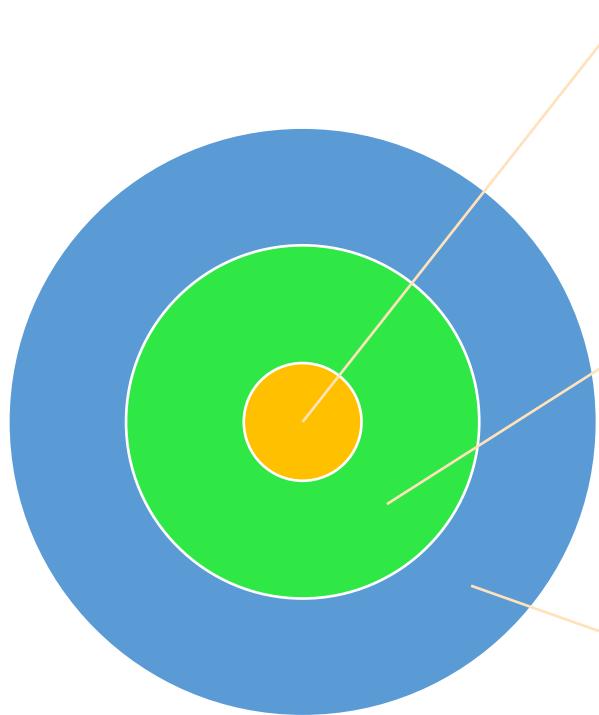
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# Overview



## Training and Loss

**Dataset:** develop a training data comprising of coarse and fine meshes with bijective mappings between them

**$l^2$  loss:** distance between each predicted vertex position at every level of subdivision and its corresponding point on the original shape

## Data Generation

each subdivided mesh at any level can be mapped back to the initial coarse mesh

## Network Architecture

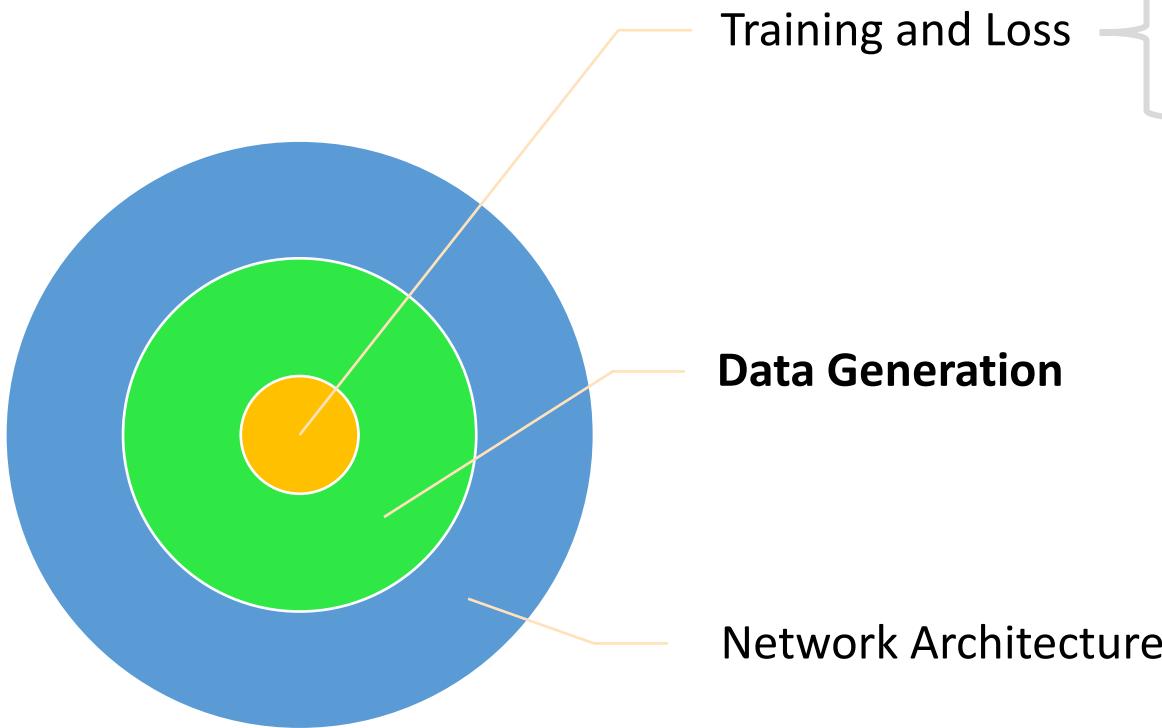
Initialization step

Vertex step

Edge step



# Overview



Training and Loss

Data Generation

Network Architecture

**Dataset:** develop a training data comprising of coarse and fine meshes with bijective mappings between them

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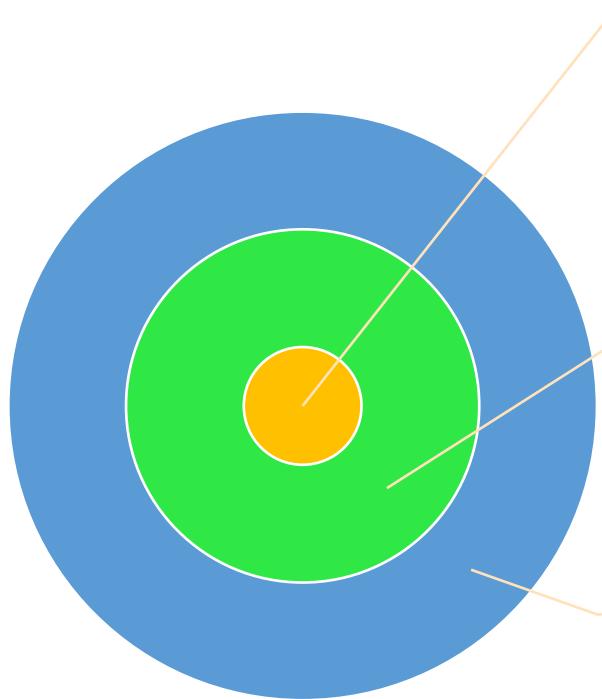
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# Overview



Training and Loss

Data Generation

Network Architecture

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**Initialization step**

**Vertex step**

**Edge step**



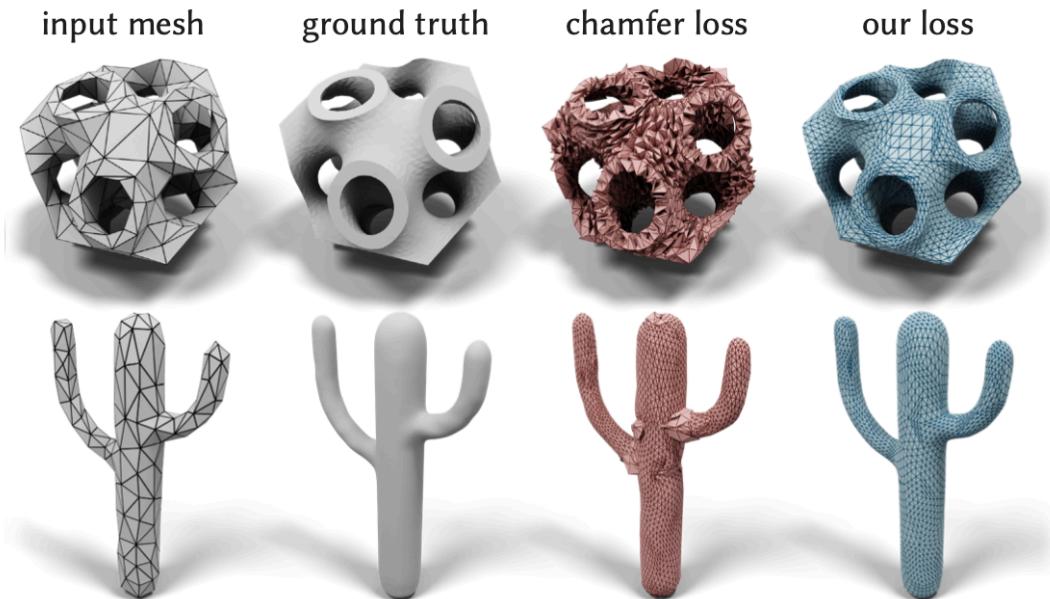
# Training and Loss

## 【Naive Subdivision Training】

- Random sampling pairs of coarse/fine meshes
- measure the distance between the network's predicted subdivision and the ground truth
- iterate over coarse/fine pairs while optimizing the loss

## 【Chamfre Loss】

point-to-mesh distance

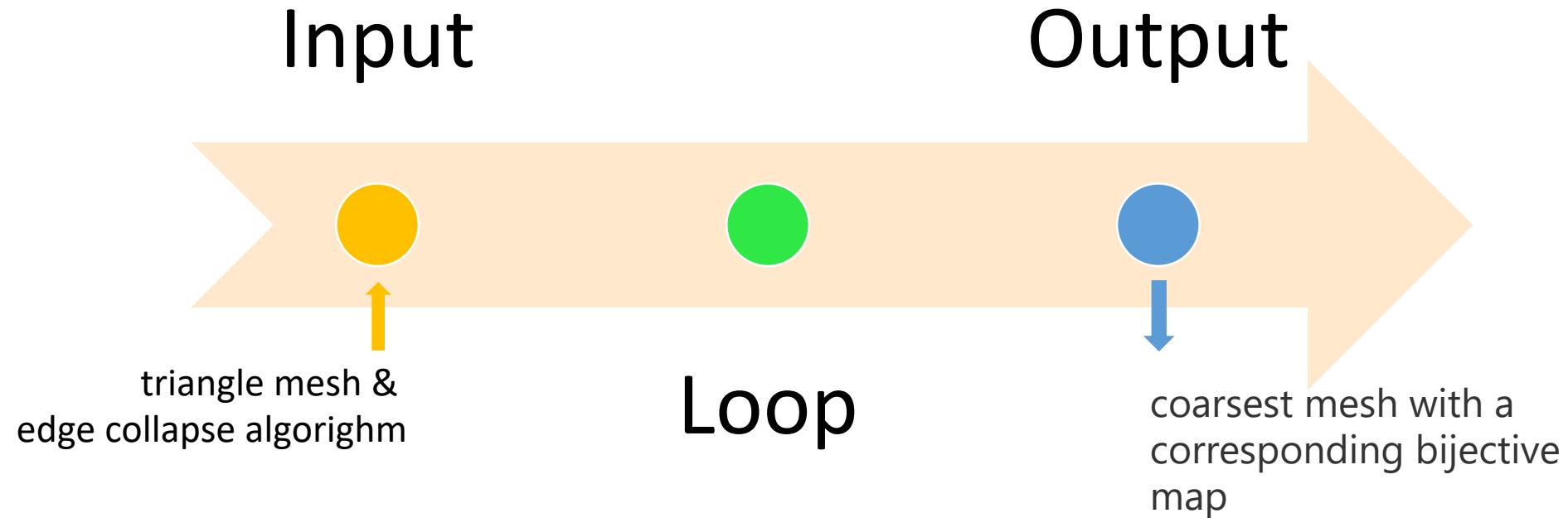




# Data Generation

## 【Successive Self-Parameterization】

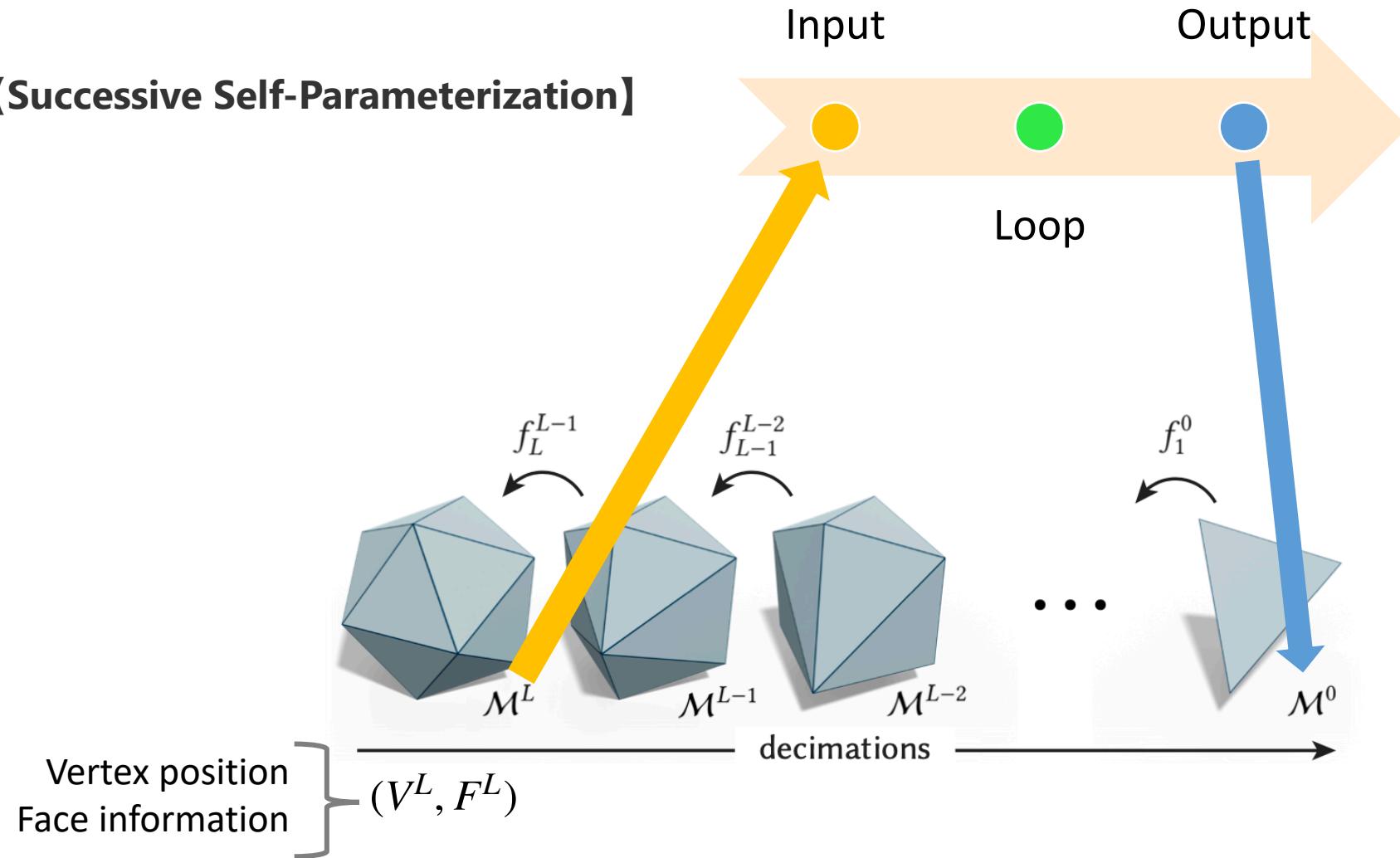
- construct a map between different discretizations of the same shape
- combine MAPS and successive mapping

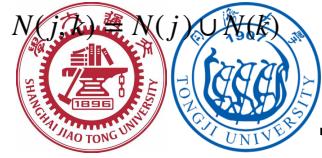




# Data Generation

## 【Successive Self-Parameterization】





# Data Generation

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## 【Single Edge Collapse】

- construct a map between different discretizations of the same shape
- combine MAPS and successive mapping

$N(i)$  neighboring vertices of a vertex i

$N(j, k) = N(j) \cup N(k)$  neighboring vertices of an edge (j,k)



# Data Generation

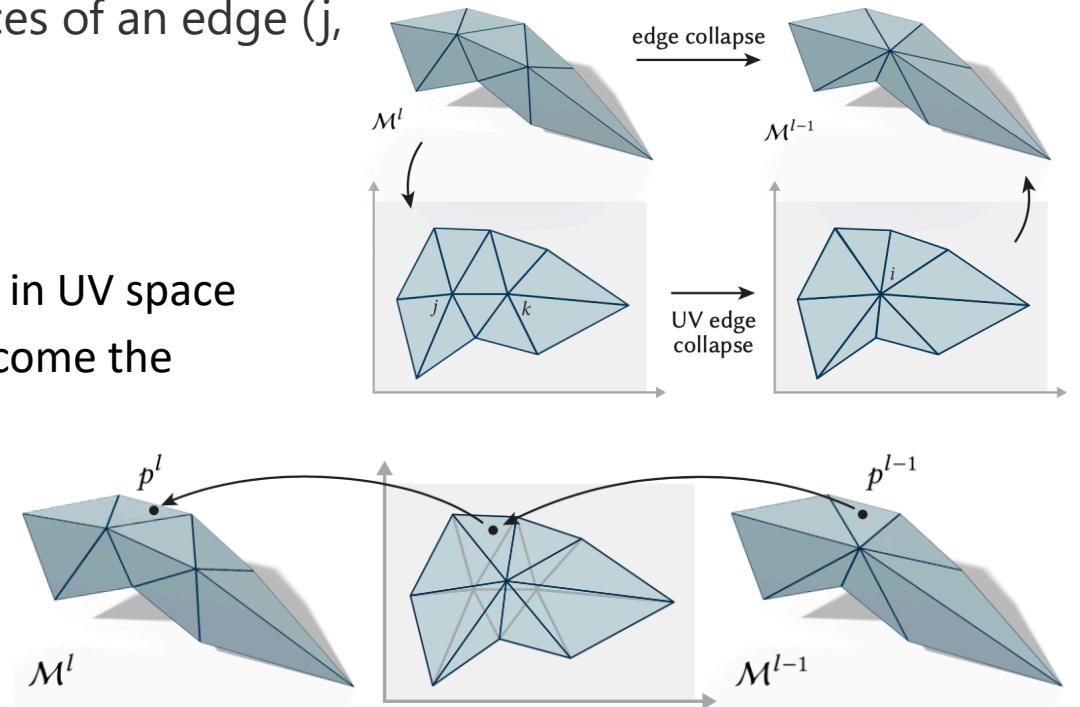
## 【Single Edge Collapse】

$N(i)$  neighboring vertices of a vertex  $i$

$N(j, k) = N(j) \cup N(k)$  neighboring vertices of an edge  $(j, k)$

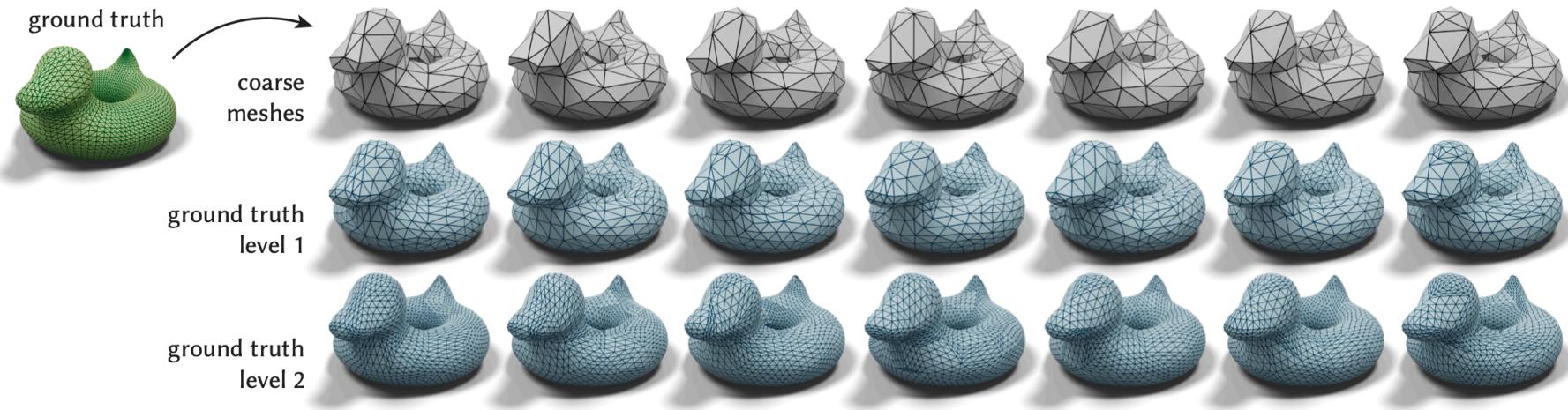
1. parameterize the neighborhood  $N(j, k)$  into 2D
2. perform the edge collapse both on the 3D mesh and in UV space
3. boundary vertices of  $N(j, k)$  before the collapse become the boundary vertices of  $N(i)$  after the collapse

- ✓ Edge collapse algo.  $\rightarrow O(N \log N)$
- ✓ Flatten  $\rightarrow$  constant cost
- ✓ Total successive self-parameterization  $\rightarrow O(N \log N)$





# Training and Loss



1. use QSLIM with a random sequence of edge collapses to construct several different decimated models
2. plug in self-parameterization to obtain a high-quality bijective map for each coarse and fine pair
3. use Loop topology to retrieve the correspondences
4. use barycentric coordinates  $b$  on the coarse mesh to obtain  $f(b)$  on the fine mesh
5. use  $l^2$  distance  $\|f(b) - \epsilon(b)\|_2$  to measure per-vertex loss



# Network Architecture

operate over atomic **local** mesh neighborhoods and predict differential features



invariant



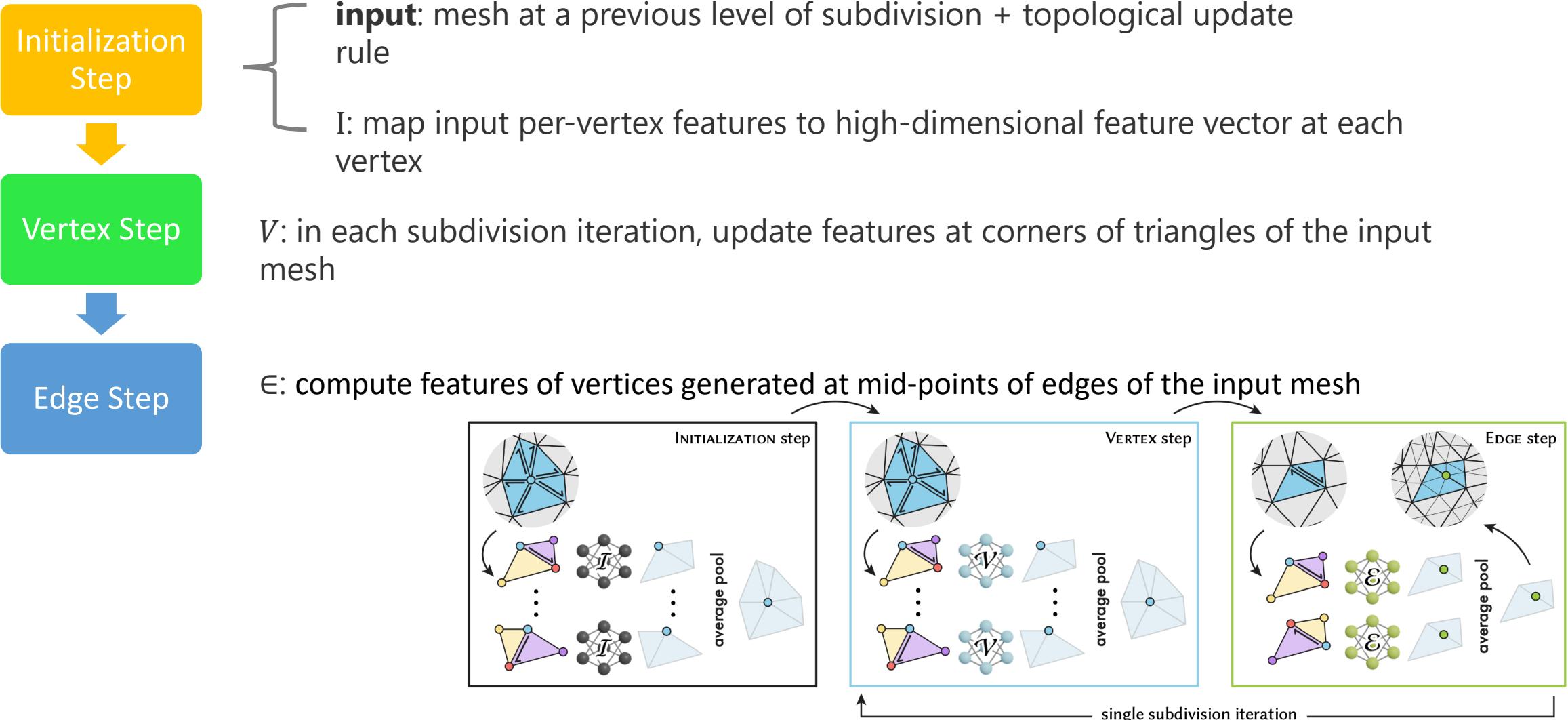
Model I is applied to the 1-ring neighborhood of every vertex to map to a *high-dimensional feature vector*

Use  $V$  to predict vertex features based on 1-ring neighborhood

Use the module  $\in$



# Network Architecture

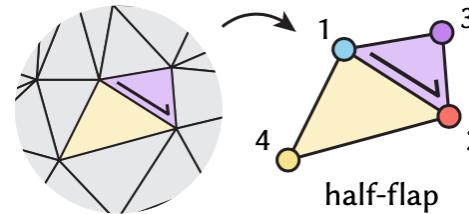




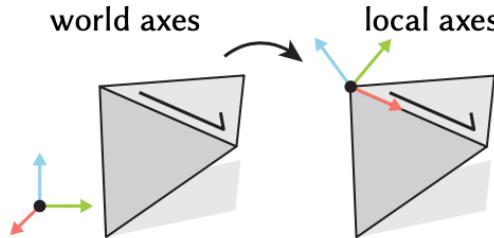
# Network Architecture

## 【Half-Flap】

Component of neural model



- x-axis: half-edge direction
- z-axis: average two adjacent face normal to get edge normal
- y-axis: cross product

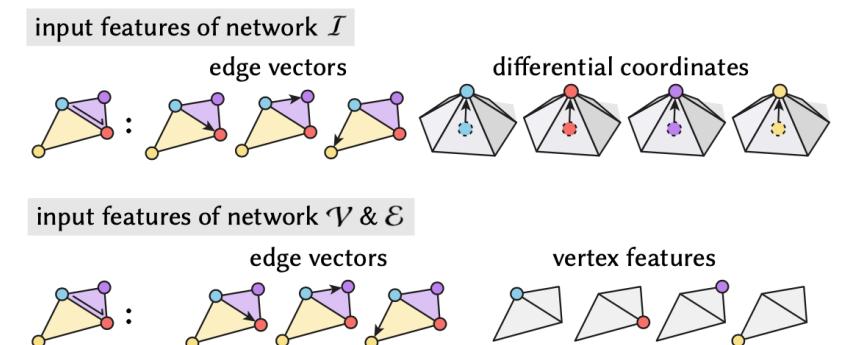


## 【Input】

- $I$  : three edge vectors and differential coordinates of each vertex(discrete curvature information)
- $V$  and  $\in$  : edge vectors and per-vertex high-dimensional learned features

## 【Output】

- $V$  and  $\in$  : high-dimensional learned features and differential quantities that can be used to reconstruct the vertex position





# Network Architecture

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## 【Classical Subdivision Algorithm】

- even vertices from previous iterations
- newly inserted odd vertices
- different: paper apply  $V$  and  $\in$  in sequence, instead of parallel. in order to harness neighborhood information from previous steps

## 【Design choices】

- operate over local mesh patches and share weights rather than global => even a single training pair provides many local mesh patches to train our neural modules
- mesh discretization: don't require re-parameterizing or re-sampling the surface
- represent vertices using differential quantities to a local coordinate frame instead of using global coordinates => invariant



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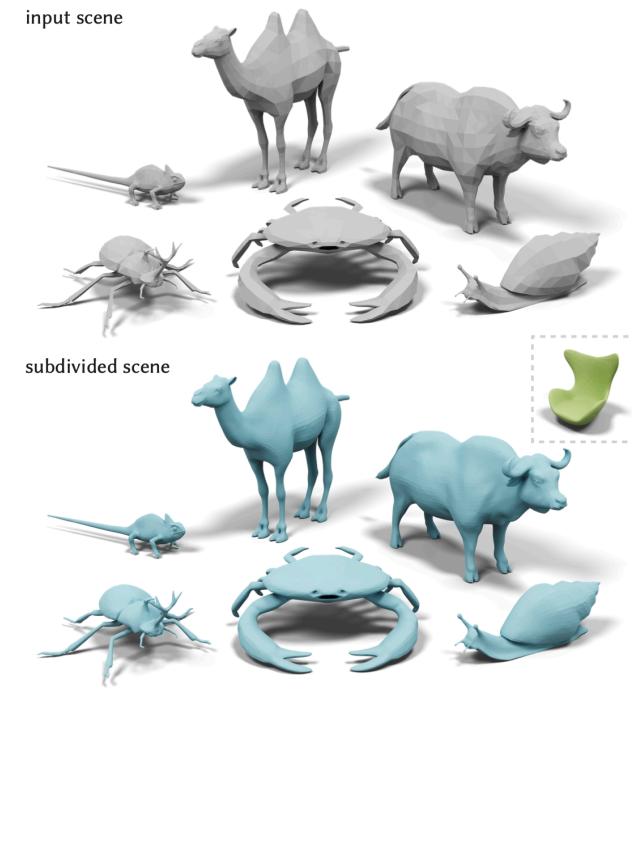
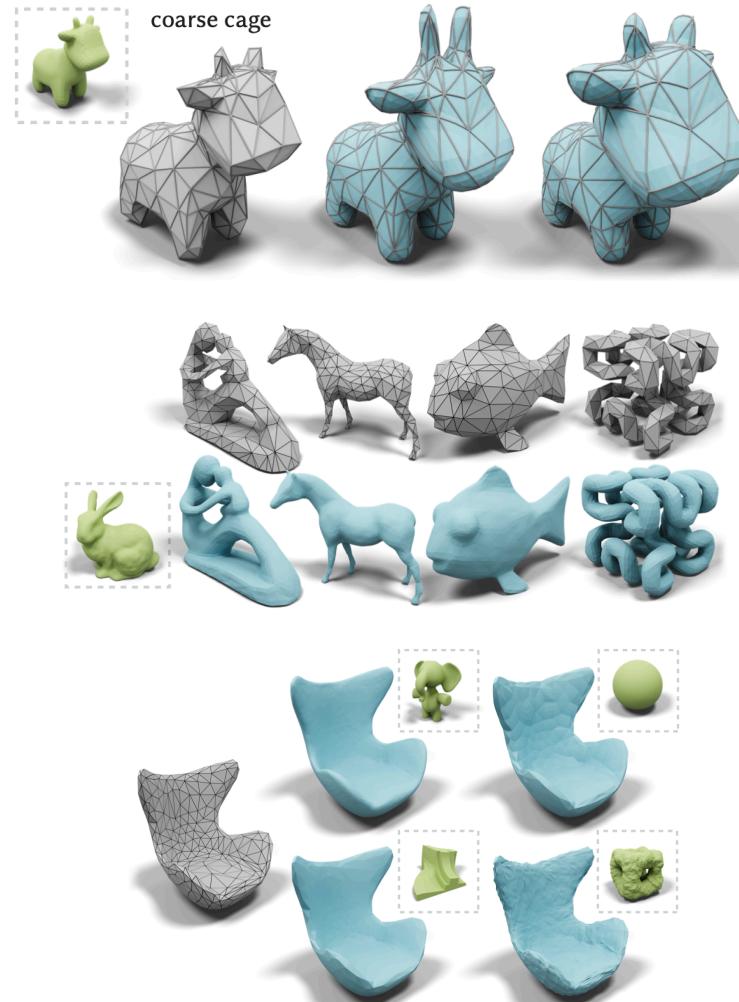
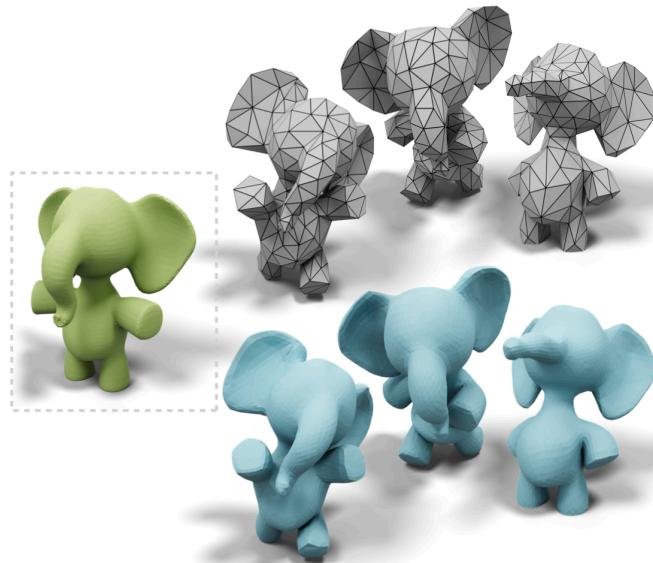
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# Evaluations

- isometric deformations
- non-isometric deformations
- shapes from different classes
- shapes from different types of discretizations
- multiple shapes and categories





# Evaluations

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- non-linear subdivision beyond simple linear averaging used in classical techniques
- only requires a set of high-resolution meshes for learning network weights
- output is a surface mesh with deterministic connectivity based on the input, enabling direct use in the standard graphics pipelines such as texture mapping
- ensure rotation and translation invariance(encode vertex position data in a local frame rather than the entire shape)
- refine the mesh locally, input could be arbitrary
- don't require co-aligned training data with a well-defined object space
- output is translation and rotation invariant(describe in local coordinate system)



# Limitations & Further Work

- Non usage of global information
- Non usage information from a wider neighborhood and to dive to a deeper subdivision level
  
- quadrilateral meshes
- surface with boundaries

