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# Implicit Representation Learning of Coronary Artery Vessels using Deep Generative Models

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# Outline

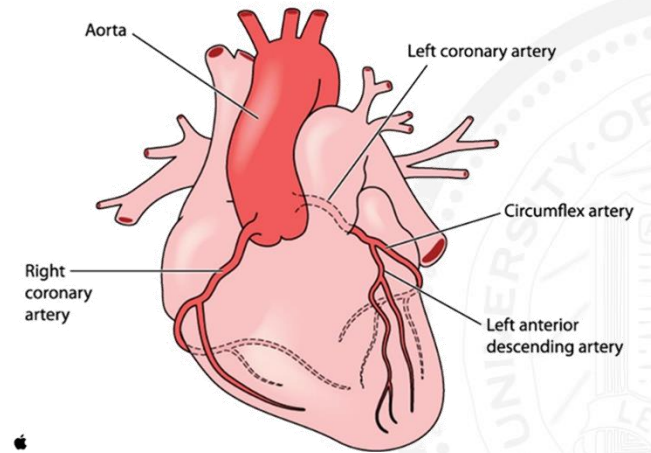
- Introduction
- Related Work
- Method
- Result



# Introduction

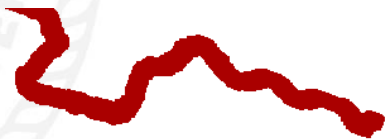
- Cardiovascular diseases have the **highest mortality** in the world, posing extremely **high risks and societal burdens**.
- Analyzing the **geometry and structure** of coronary artery is important for **downstream tasks**, such as coronary artery segmentation.
- our objective is to develop a **point cloud generative model** to learn the Implicit representation of coronary artery dataset.

## Coronary Arteries



# Introduction

- modeling coronary artery dataset is a **challenging task** due to the **complexity** of the vascular system.
  - a. the complex **geometric** bending degree
  - b. intricate branching **structures**
  - c. significant **variations** among different samples



a. bending degree



b. branching structure



c. variations among samples

# Outline

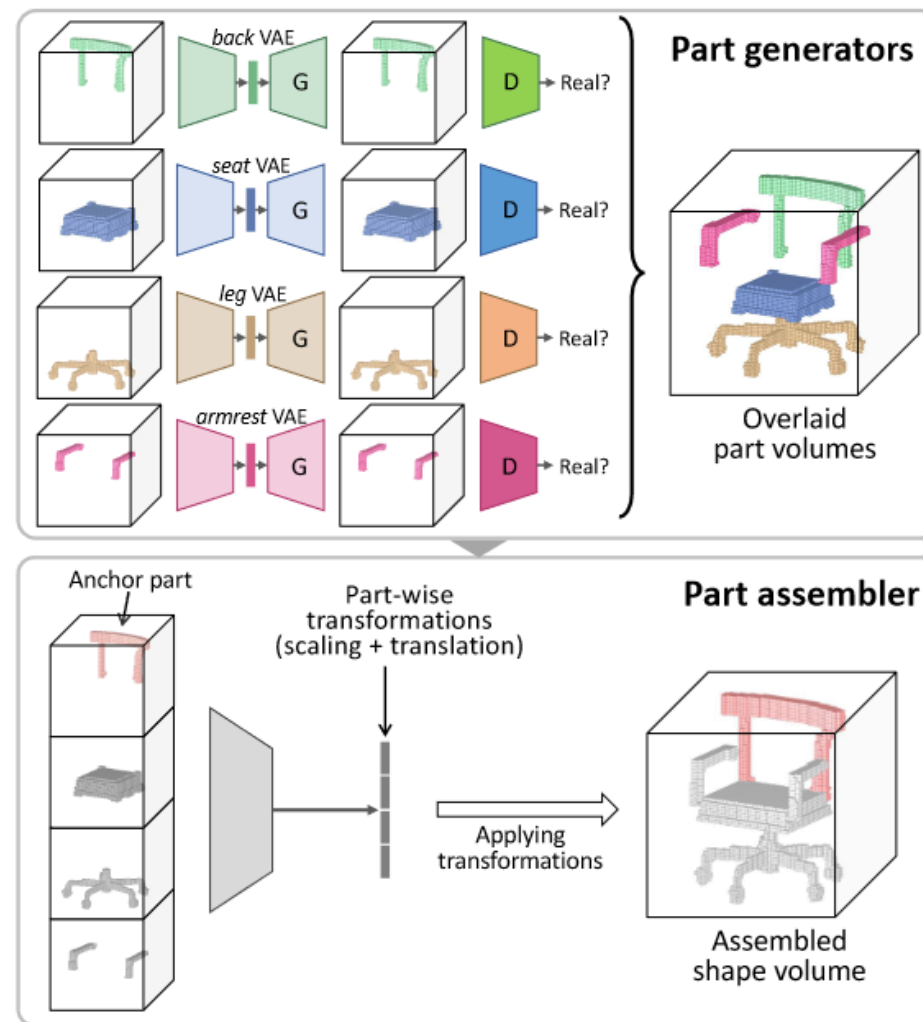
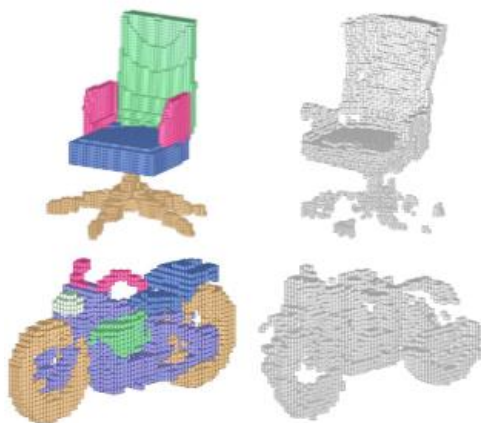
- Introduction
- **Related Work**
  - ✓ Part-based Generative Model
  - ✓ Disentangled Representation Learning
- Method
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# Related Work

## ➤ Part-based generative model

Unlike holistic model, part-based generative model **generates each part separately** and **then assemble** them together.

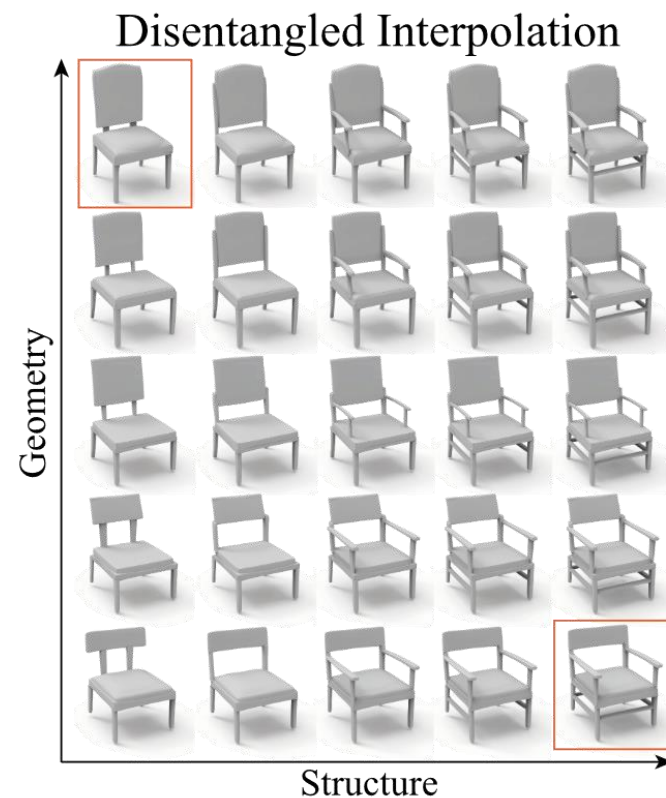
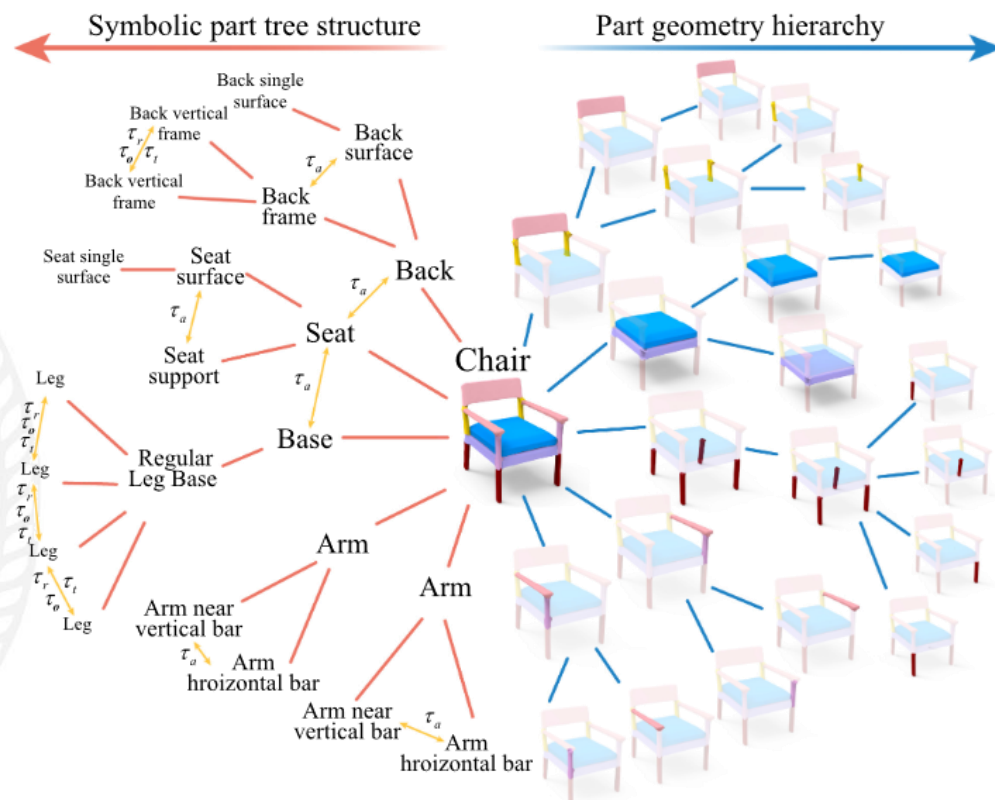
It can Improve the ability to model complex objects.



# Related Work

## ➤ Disentangled Representation Learning

Disentangled representation aims to learn **different aspects** of data independently, so as to capture **different factors or features** in data.



Modeling the **geometry and structural** information of objects separately.

# Outline

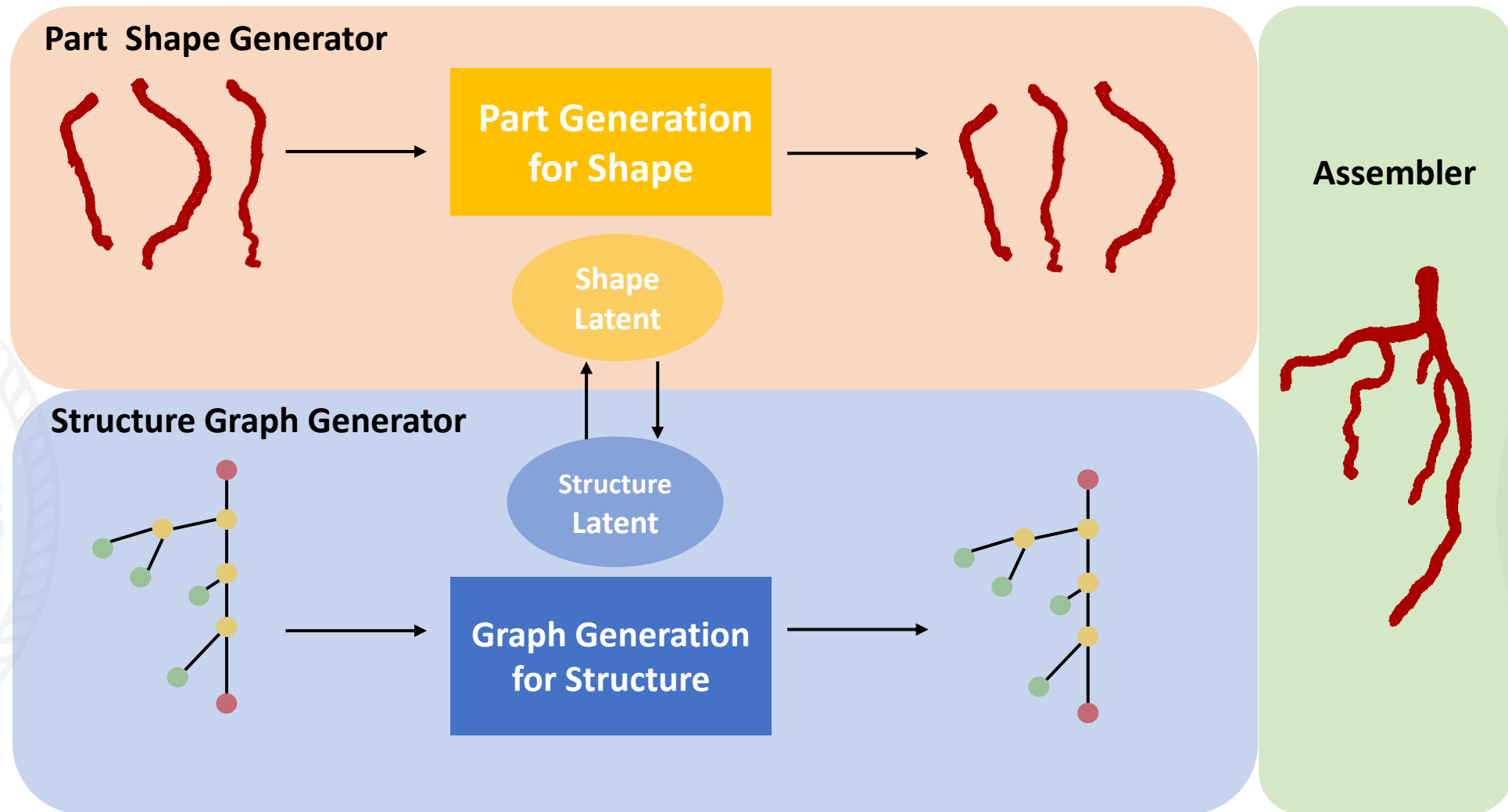
- Introduction
- Related Work
- **Method**
  - ✓ Part Shape Generation
  - ✓ Structure Graph Generation
- Result





# Method

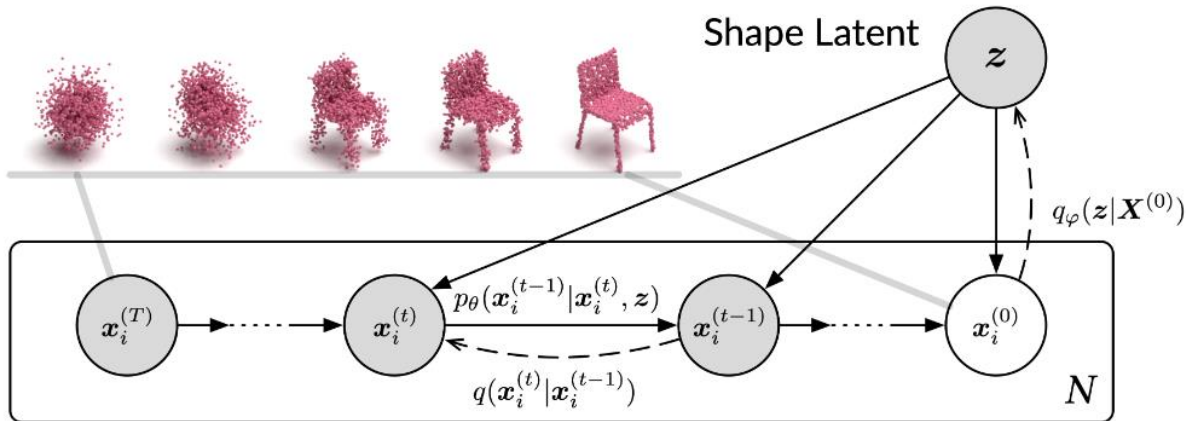
## ➤ Model Architecture



# Method

## ➤ Part Shape Generator

### Diffusion Probabilistic Models for 3D Point Cloud Generation



**Forward diffusion process: add noise**

$$q(x^{(1:T)} | x^{(0)}) = \prod_{t=1}^T q(x^{(t)} | x^{(t-1)})$$

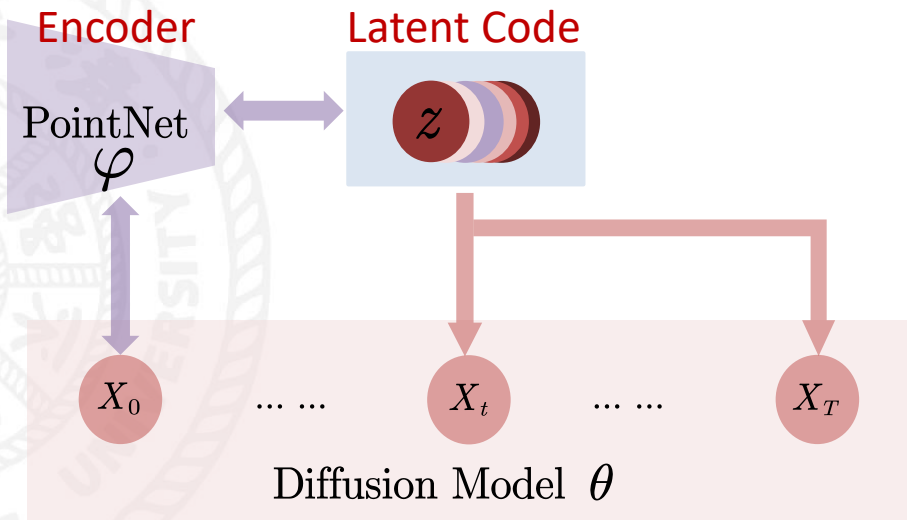
**Reverse diffusion process: denoise**

$$p_\theta(x^{(0:T)} | z) = p(x^{(T)}) \prod_{t=1}^T p_\theta(x^{(t-1)} | x^{(t)}, z)$$

# Method

## ➤ Part Shape Generator: Diffusion Probabilistic Models for 3D Point Cloud Generation

1. We use PointNet as the encoder to model the shape latent  $z$
2. the shape latent  $z$  as a **conditional variable** guides the reverse process of each step.



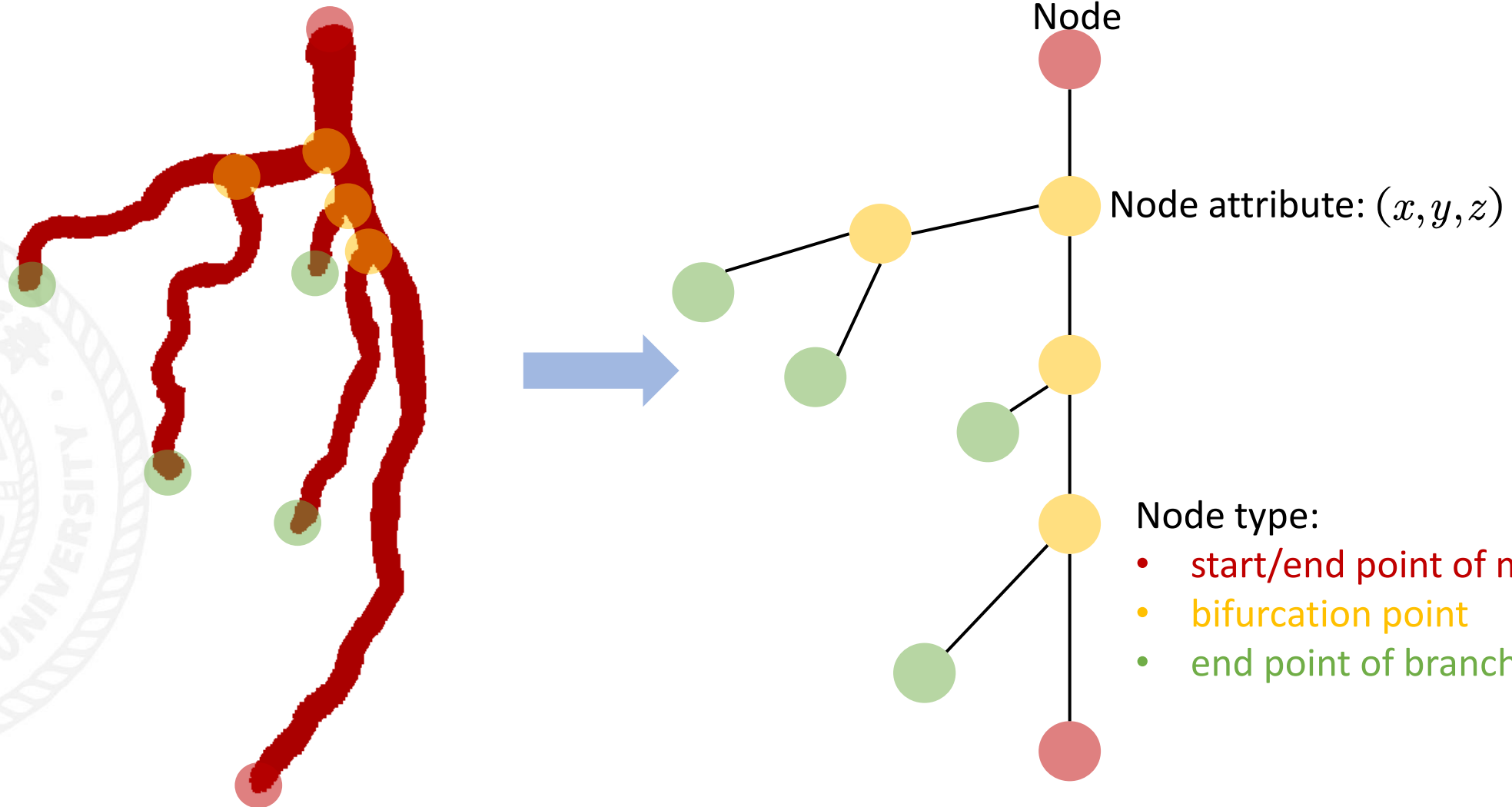
### Loss Function:

$$L(\theta, \varphi) = \mathbb{E}_q \left[ \sum_{t=2}^T \sum_{i=1}^N D_{KL} \left( q(x_i^{(t-1)} | x_i^{(t)}, x_i^{(0)}) \parallel p_{\theta}(x_i^{(t-1)} | x_i^{(t)}, E_{\varphi}(X^{(0)})) \right) - \sum_{i=1}^N \log p_{\theta}(x_i^{(0)} | x_i^{(1)}, E_{\varphi}(X^{(0)})) \right]$$

Latent code  $z$

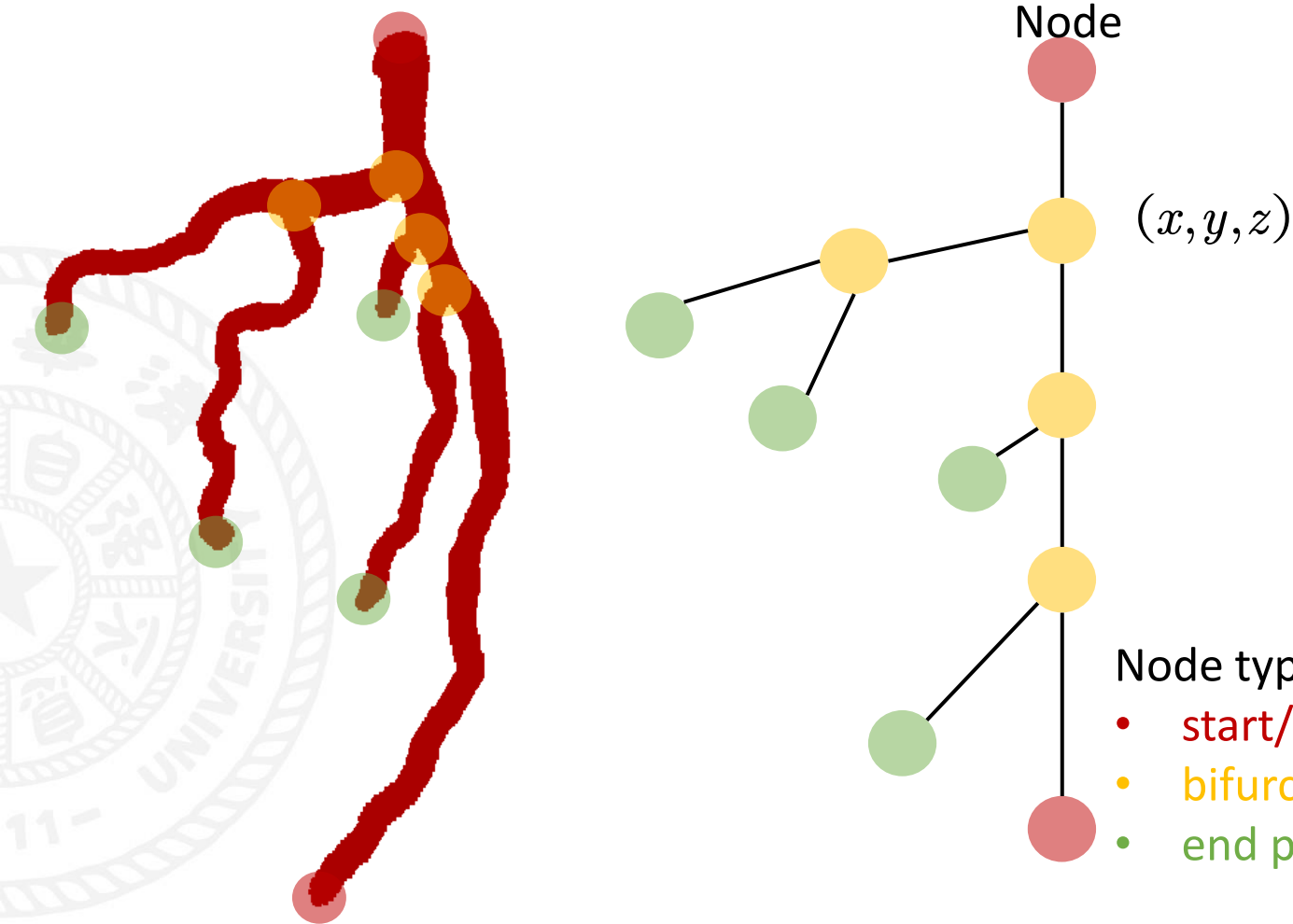
# Method

## ➤ Structure Graph Generator: Key Points Graph



# Method

## ➤ Structure Graph Generator: Key Points Graph



The information in the graph:

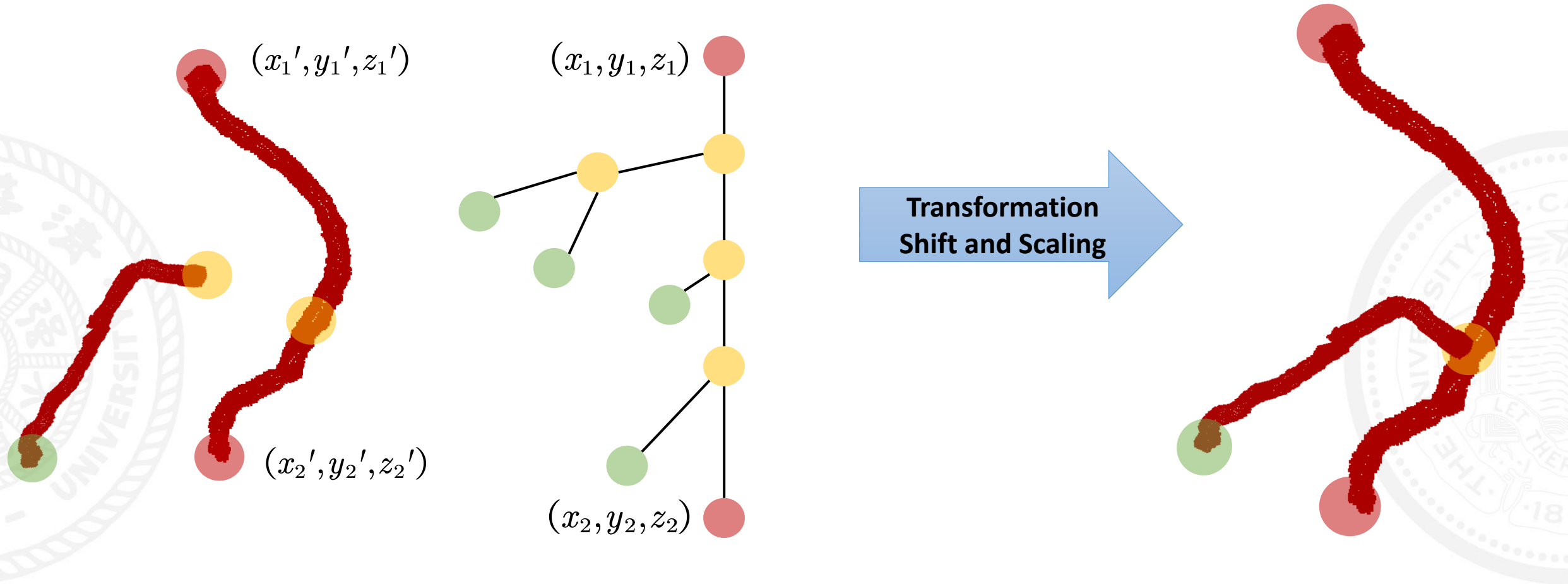
1. The number of branches
2. The direction of each branch
3. The length of each branch

Node type:

- start/end point of main branch
- bifurcation point
- end point of branch

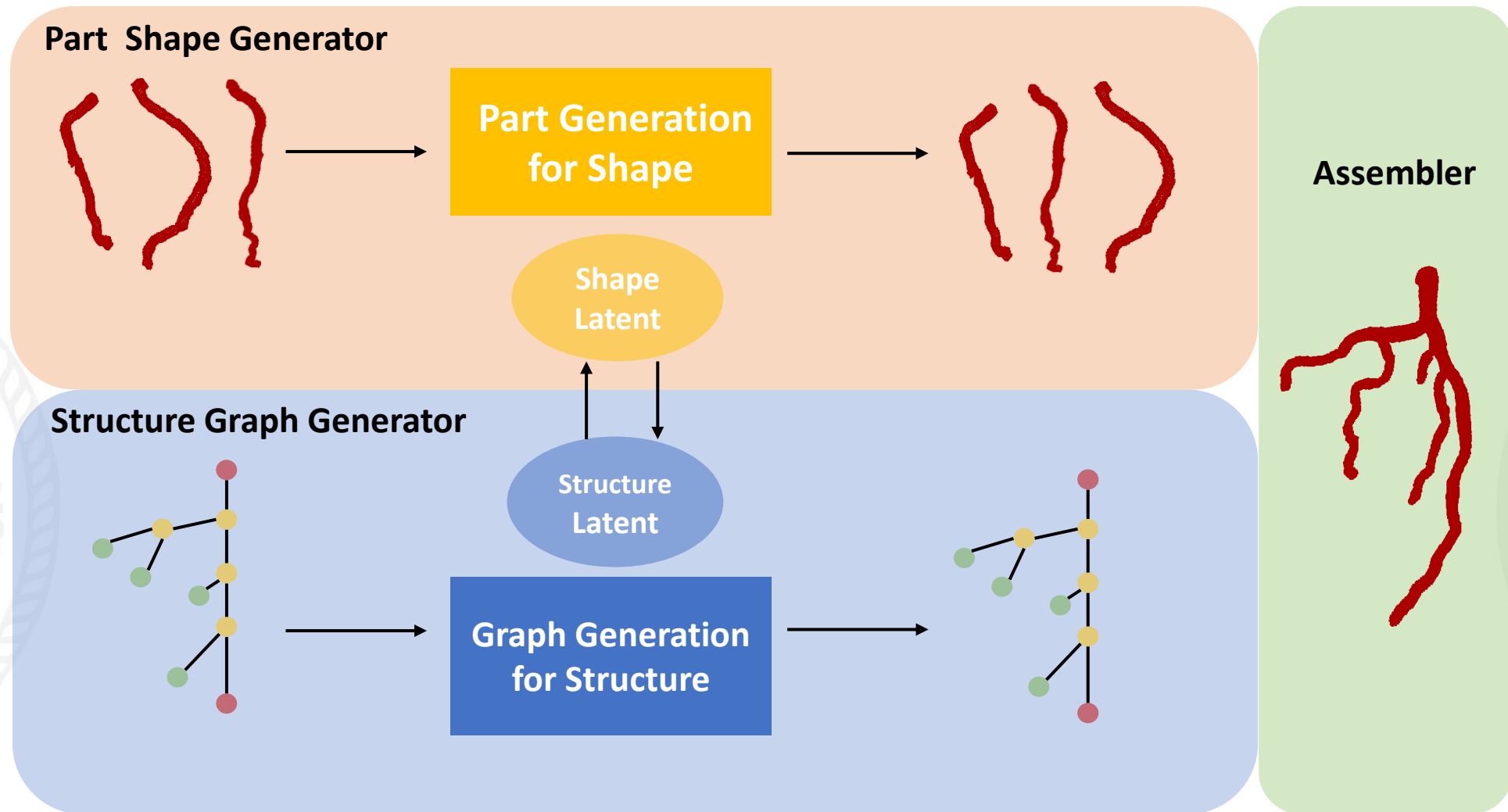
# Method

## ➤ Assembler



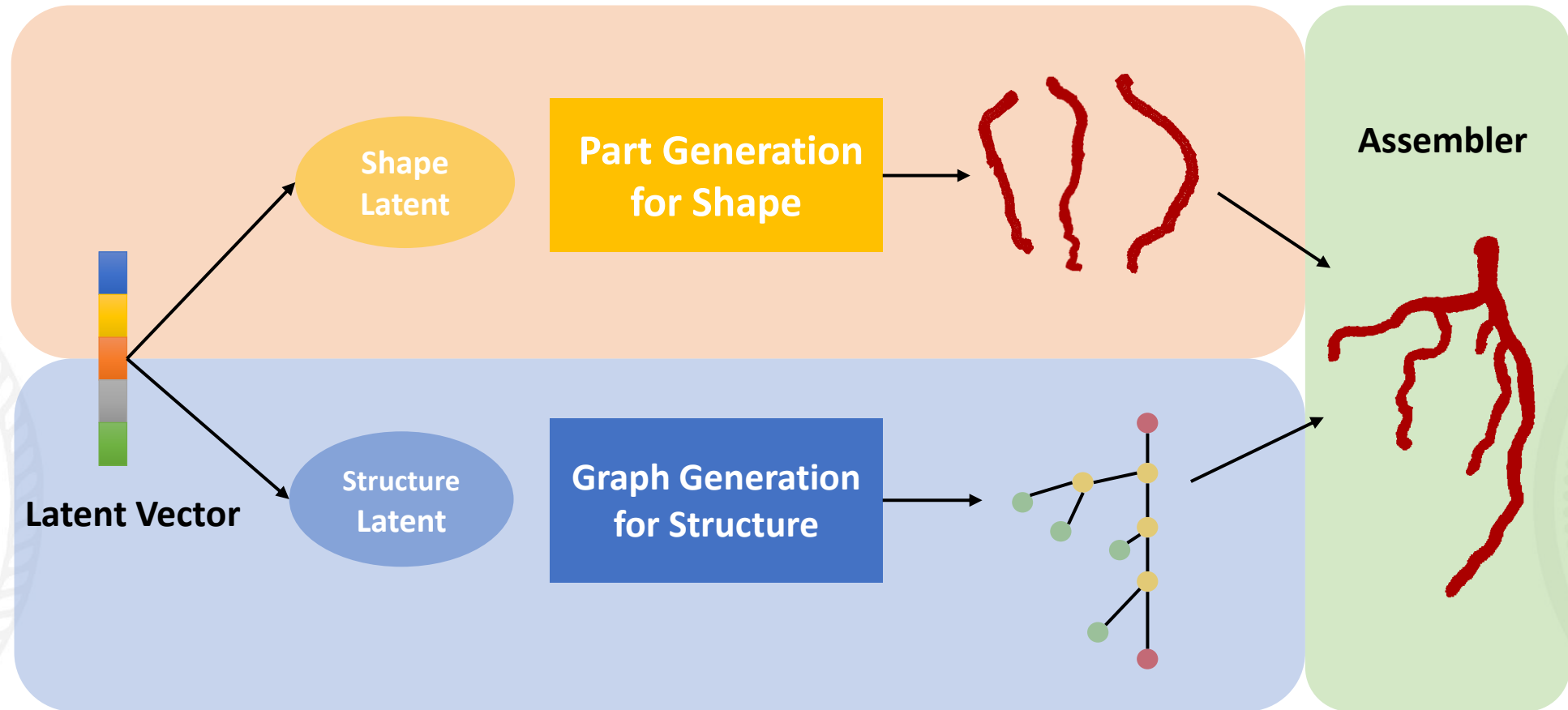
# Method

## ➤ Train



# Method

## ➤ Sample





# Outline

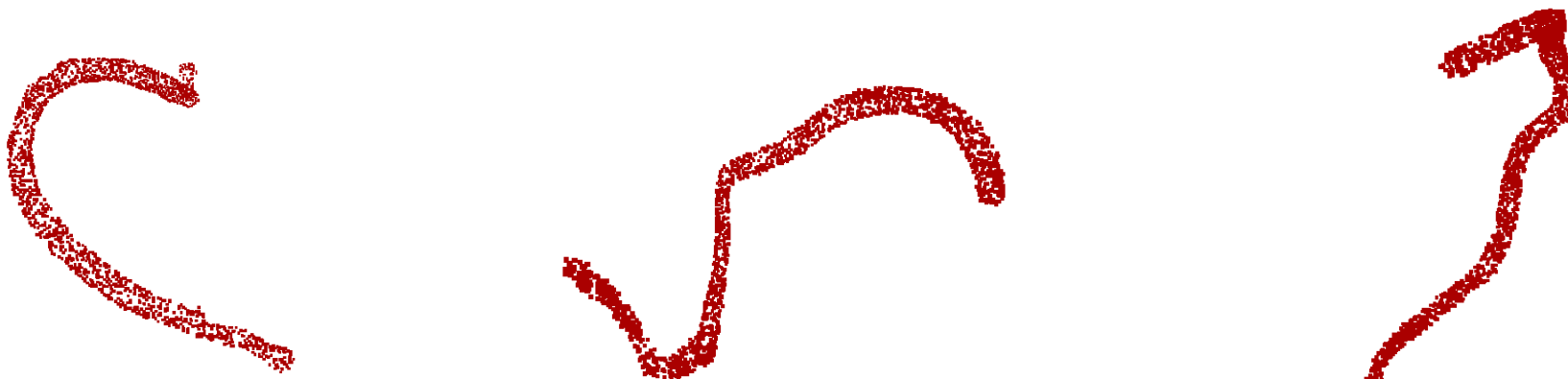
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- **Result**
  - ✓ Geometry Shape Generation



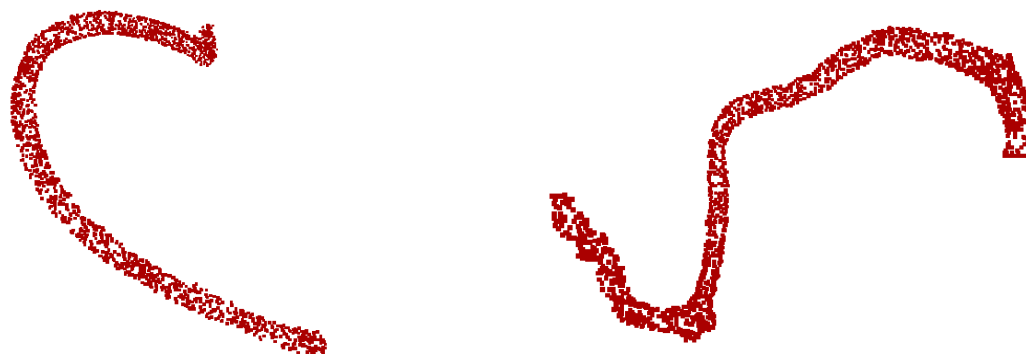
# Result

- the result of training each branch separately using the point cloud diffusion model

**Reconstructed**



**Original**



# Discussion

Next step:

- Modify the Part Shape Generator and turn it into **label conditional** generator.
- Establish the **key point graph**
- Implementing the **Structure Graph Generator**.

# Discussion

THANK YOU  
Q & A

