



# Reinforcement Learning

Point Cloud Shape Completion by using RL-GAN-Net

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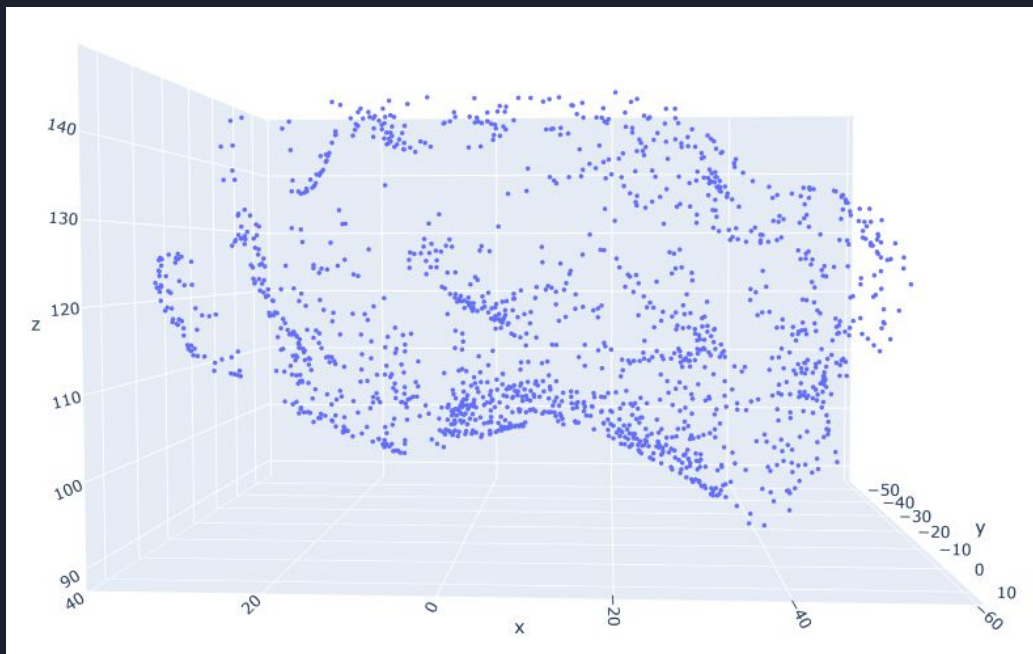
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# Outline

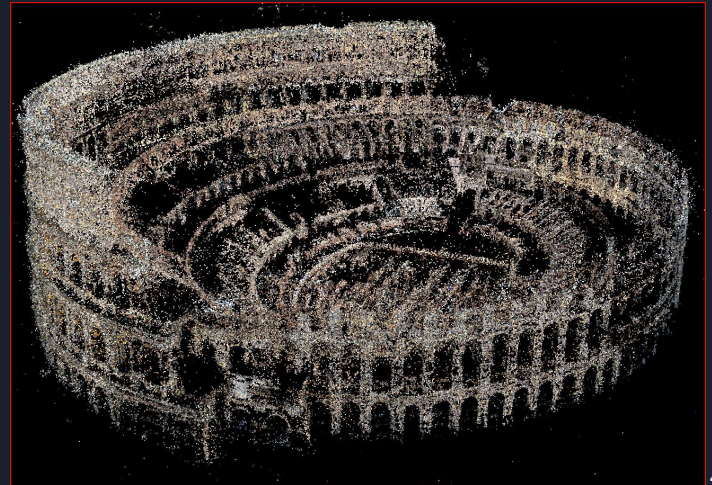
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1. Point Cloud: a presentation data type
2. Project Real-time Point Cloud Shape Completion by using RL-GAN-Net
3. Beside content: AutoEncoder and GAN in Machine learning
4. Reinforcement Learning method
5. Result
6. Overview conclusion



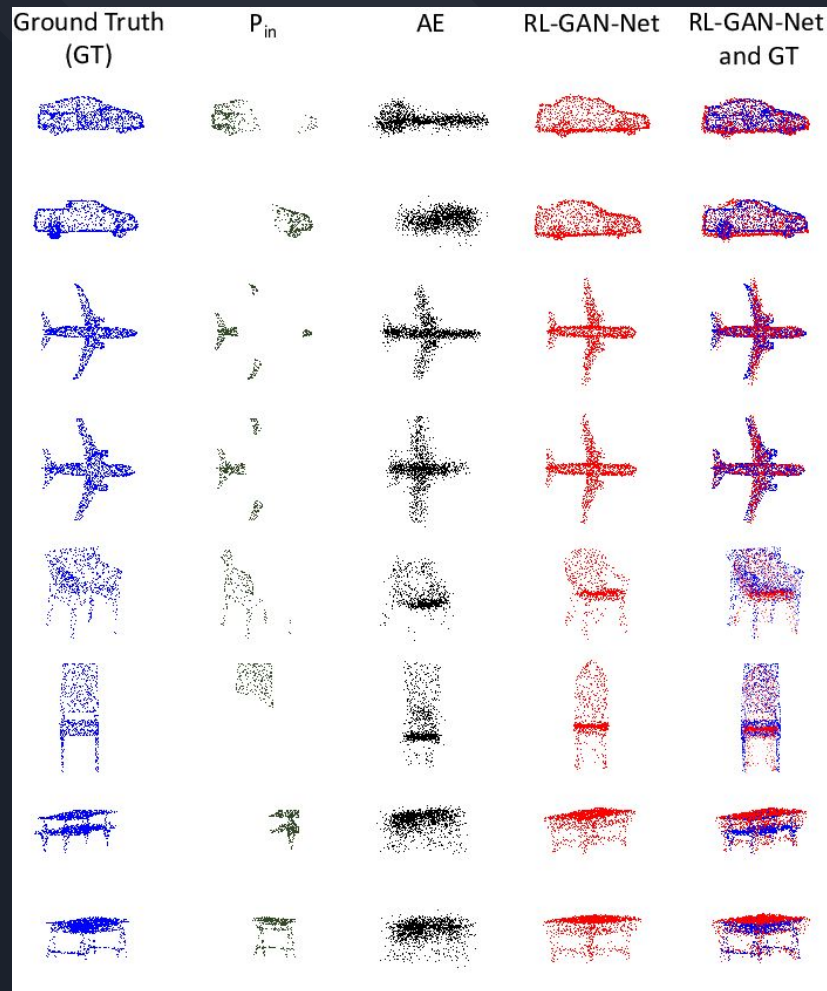
Point Cloud: a presentation data type

- Đại diện cho đối tượng hoặc không gian
- Biểu diễn trong hệ tọa độ XYZ
- Khi có thông tin màu sắc (RGB), đám mây điểm sẽ trở thành 4D
- Mật độ point/mm<sup>2</sup>
- Độ chính xác 1 point/... mm
- Vector khoảng cách từ góc nhìn (hình ảnh)
- Thư viện PCL mã nguồn mở, các module hỗ trợ cho các nền tảng khác
- Tồn thời gian scan và process
- Phát triển phù hợp thay thế các phương pháp lưu trữ truyền thống.



Point Cloud: a presentation data type

# Point Cloud Shape Completion





← → ↺ arxiv.org/abs/1904.12304

Cornell University

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Computer Science > Computer Vision and Pattern Recognition

[Submitted on 28 Apr 2019]

## RL-GAN-Net: A Reinforcement Learning Agent Controlled GAN Network for Real-Time Point Cloud Shape Completion

Muhammad Sarmad, Hyunjoo Jenny Lee, Young Min Kim

We present RL-GAN-Net, where a reinforcement learning (RL) agent provides fast and robust control of a generative adversarial network (GAN). Our framework is applied to point cloud shape completion that converts noisy, partial point cloud data into a high-fidelity completed shape by controlling the GAN. While a GAN is unstable and hard to train, we circumvent the problem by (1) training the GAN on the latent space representation whose dimension is reduced compared to the raw point cloud input and (2) using an RL agent to find the correct input to the GAN to generate the latent space representation of the shape that best fits the current input of incomplete point cloud. The suggested pipeline robustly completes point cloud with large missing regions. To the best of our knowledge, this is the first attempt to train an RL agent to control the GAN, which effectively learns the highly nonlinear mapping from the input noise of the GAN to the latent space of point cloud. The RL agent replaces the need for complex optimization and consequently makes our technique real time. Additionally, we demonstrate that our pipelines can be used to enhance the classification accuracy of point cloud with missing data.

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Subjects: Computer Vision and Pattern Recognition (cs.CV); Artificial Intelligence (cs.AI)


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(or arXiv:1904.12304v1 [cs.CV] for this version)  
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- (1) training the GAN on the latent space representation whose dimension is reduced compared to the raw point cloud input
- (2) using an RL agent to find the correct input to the GAN to generate the latent space representation of the shape that best fits the current input of incomplete point cloud

# Real-time Point Cloud Shape Completion by using RL-GAN-Net

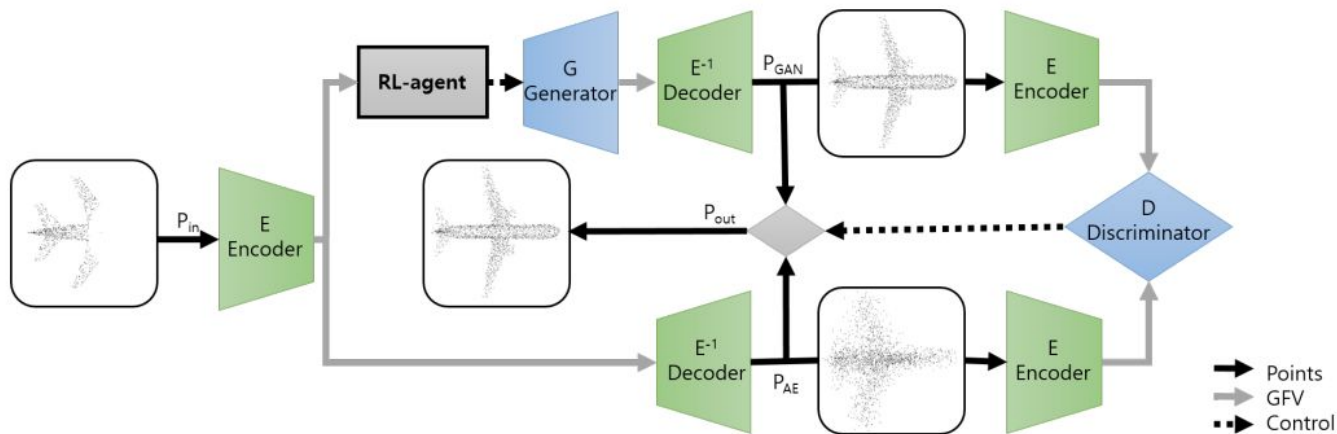
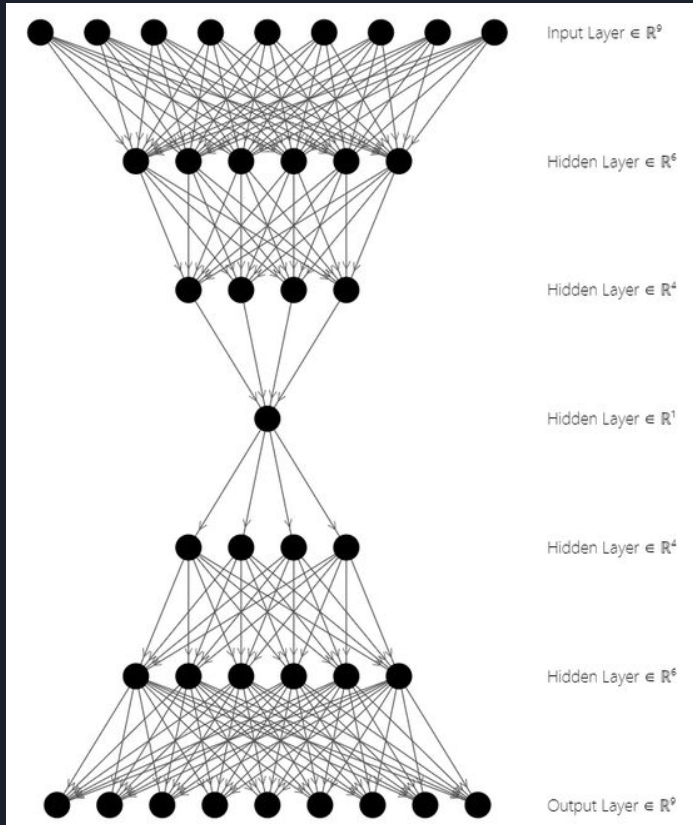


Figure 2: **The forward pass of our shape completion network.** By observing an encoded partial point cloud, our RL-GAN-Net selects an appropriate input for the latent GAN and generates a cleaned encoding for the shape. The synthesized latent representation is decoded to get the completed point cloud in real time. In our hybrid version, the discriminator finally selects the best shape.

# AutoEncoder (AE)



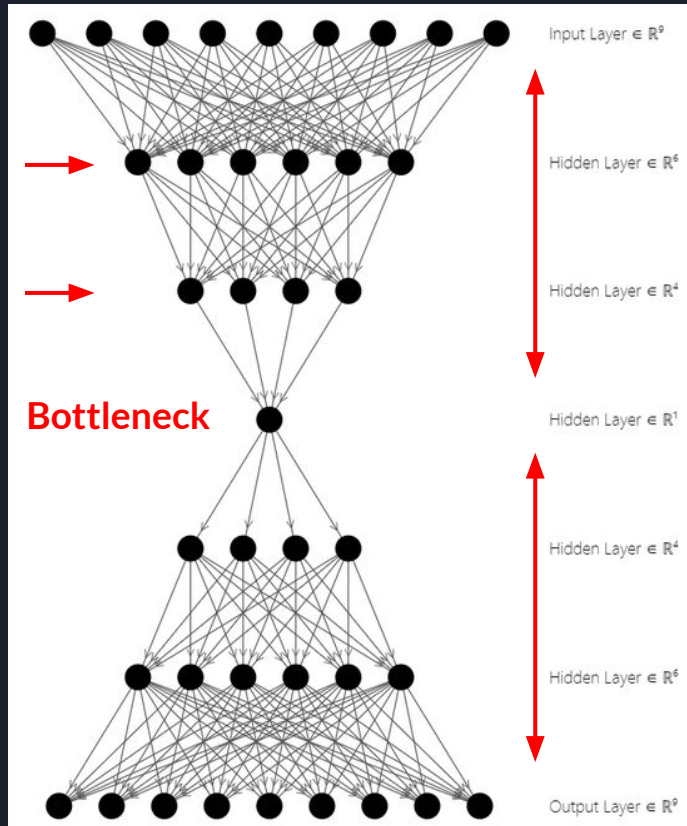
Encoder  
Structure

Latent Space  
Structure

Decoder  
Structure



# Autoencoder



Code size

Number of  
layers

Number of  
nodes per layer

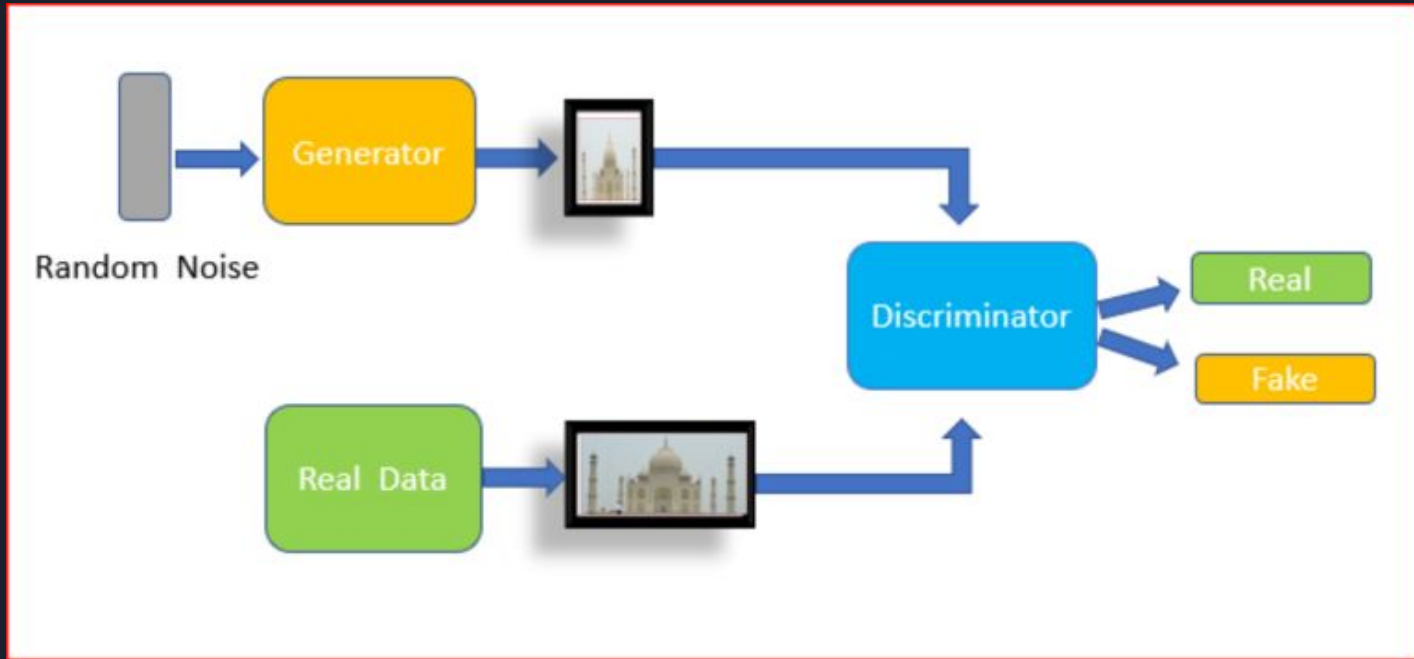
Reconstruction  
Loss

MSE

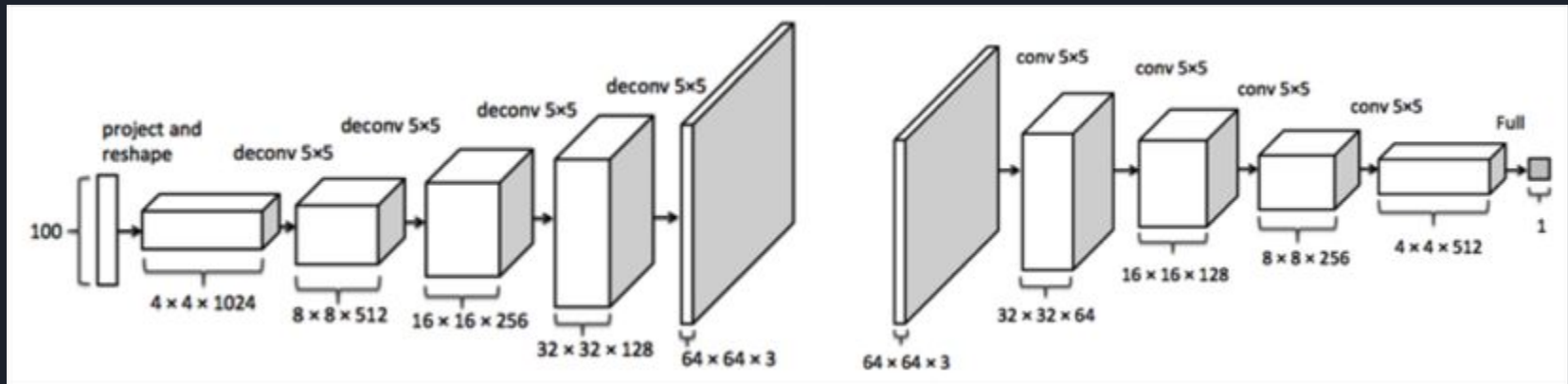
L1 Loss

Binary  
cross  
entropy

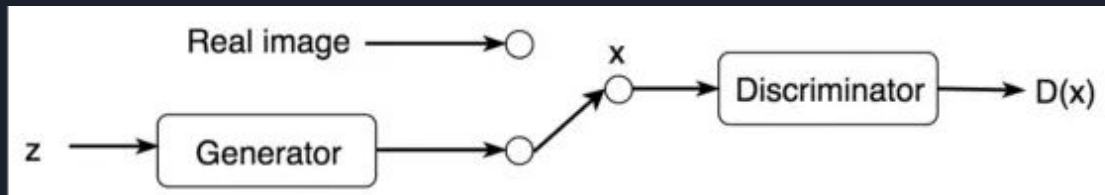
# Generative Adversarial Network (GAN)



# Deep Convolution GAN (DCGAN)



# GAN training steps



1. B1: Từ một nhiễu  $z$  bất kì,  $G$  sinh ra fake-image  $G(z)$  có kích thước như ảnh thật (ảnh thật là  $x$ ). Tại lần sinh đầu tiên,  $G(z)$  hoàn toàn là ảnh nhiễu, không có bất kỳ nội dung gì đặc biệt
2. B2:  $x$  và  $G(z)$  cùng được đưa vào  $D$  kèm nhãn đúng sai. Train  $D$  để học khả năng phân biệt ảnh thật, ảnh giả.
3. B3: Đưa  $G(z)$  vào  $D$ , dựa vào feedback của  $D$  trả về,  $G$  sẽ cải thiện khả năng fake của mình.
4. B4: Quá trình trên sẽ lặp đi lặp lại như vậy,  $D$  dần cải thiện khả năng phân biệt,  $G$  dần cải thiện khả năng fake. Đến khi nào  $D$  không thể phân biệt được ảnh nào là ảnh do  $G$  tạo ra, ảnh nào là  $x$ , khi đó quá trình dừng lại.

Discriminator D target: to maximize  $\text{Max}_D V(D)$

$$\max_D V(D) = \underbrace{\mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})]}_{\text{recognize real images better}} + \underbrace{\mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]}_{\text{recognize generated images better}}$$

Generator G target: to minimize  $\text{Min}_G V(G)$

$$\min_G V(G) = \underbrace{\mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]}$$

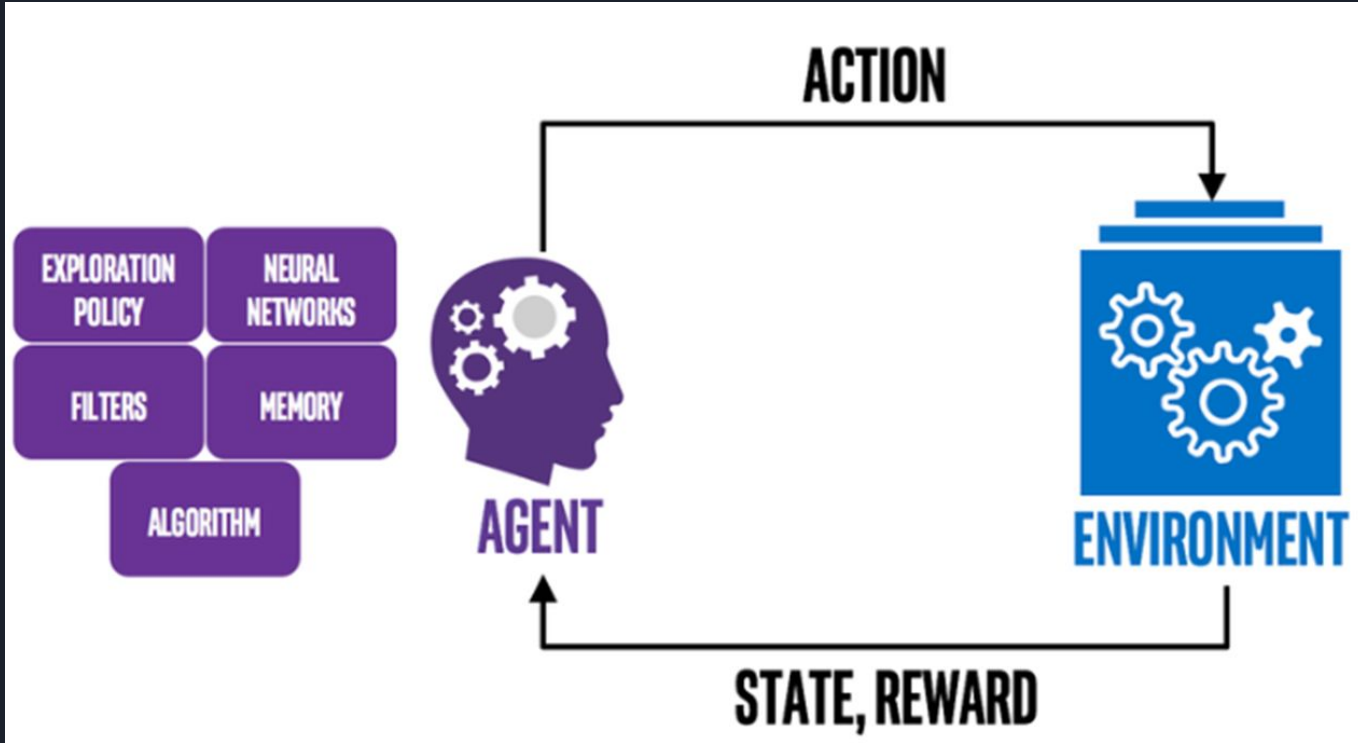
Optimize G that can fool the discriminator the most.

Finally for GAN problem

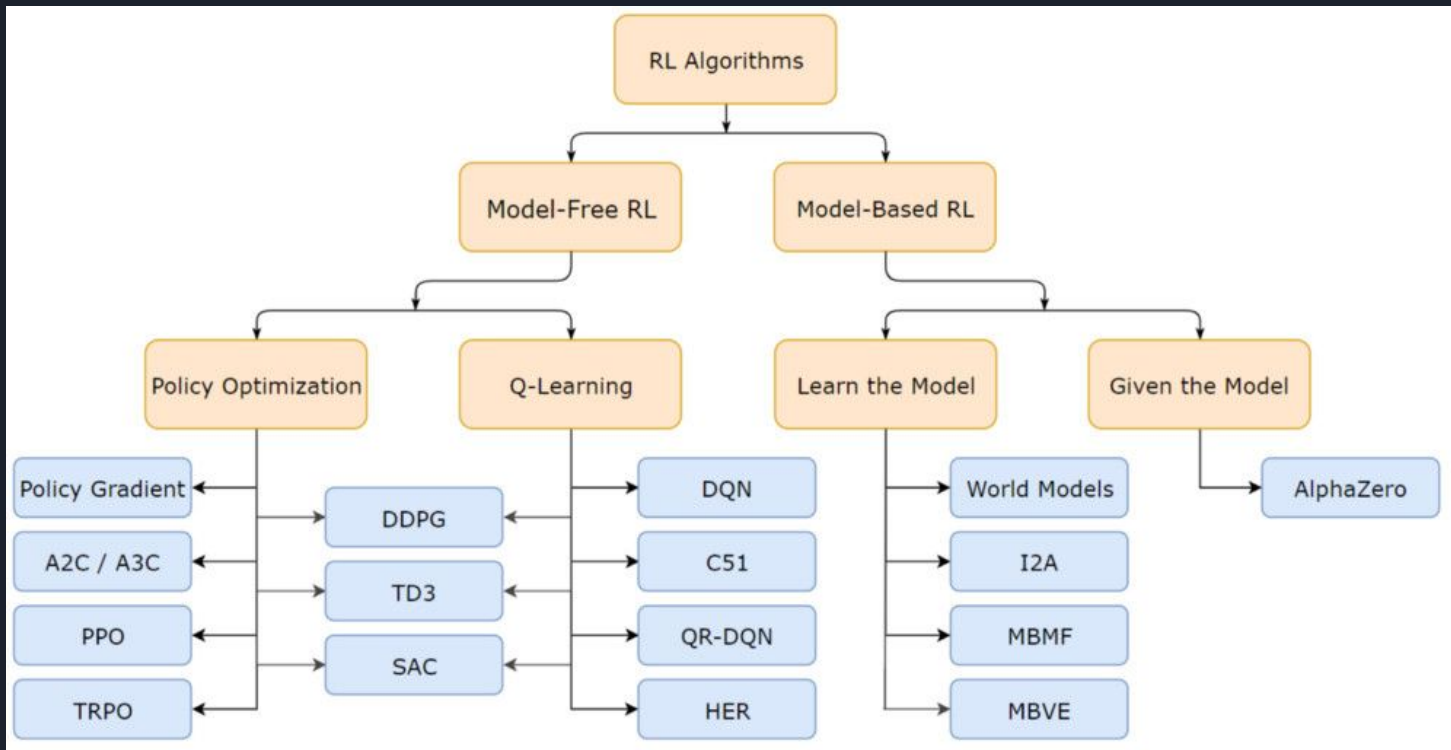
$$\min_G \max_D V(D, G) = \mathbb{E}_{\mathbf{x} \sim p_{\text{data}}(\mathbf{x})} [\log D(\mathbf{x})] + \mathbb{E}_{\mathbf{z} \sim p_{\mathbf{z}}(\mathbf{z})} [\log(1 - D(G(\mathbf{z})))]$$



# Reinforcement Learning



# Reinforcement Learning method



Environment

shape completion  
frame

Action

GAN Generator

State

initial GVF noise

Policy

actor-critic-based  
network

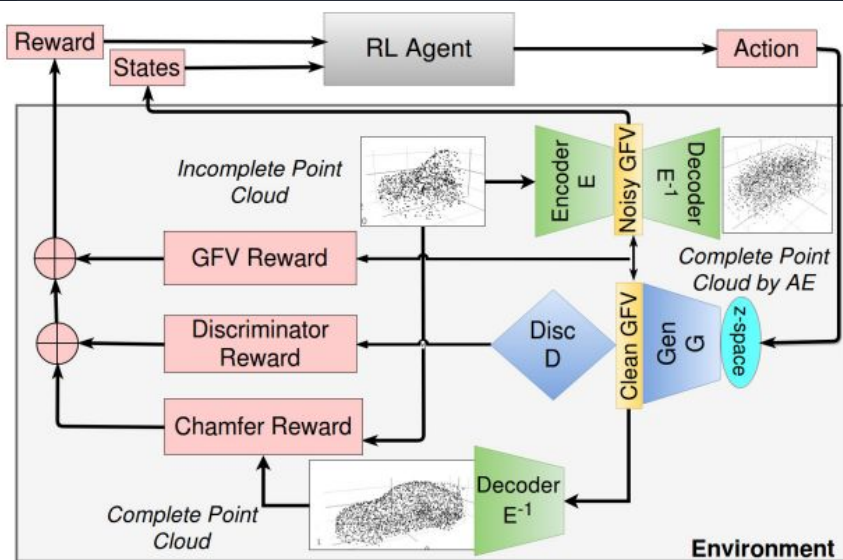


Figure 3: **Training RL-GAN-Net for shape completion.** Our RL framework utilizes AE (shown in green) and  $t$ -GAN (shown in blue). The RL agent and the environment are shaded in gray, and the embedded reward, states, and action spaces are highlighted in red. The output is decoded and completed as shown at the bottom. Note that the decoder and decoded point cloud in the upper right corner is added for a comparison, and does not affect the training. By employing an RL agent, our pipeline is capable of real-time shape completion.



# RL-GAN-Net hybrid algorithm

## Deep deterministic policy gradient (DDPG)

### Actor network $\mu(s | \theta^\mu)$

learns a particular policy and maps states to particular actions in a deterministic manner

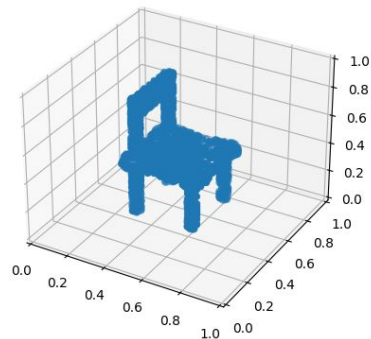
### Critic network $Q(s, a)$ uses the

Bellman equation and provides a measure of the quality of action and the state

The actor network is trained by finding the expected return of the gradient to the cost  $J$  w.r.t the actor-network parameters, which is also known as the *policy gradient*

5120\_in\_.png

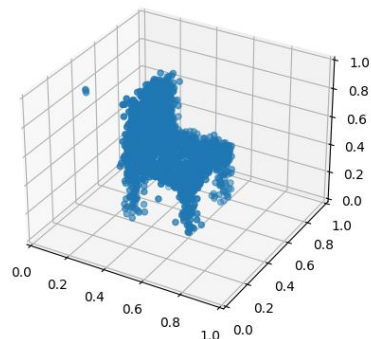
- **Dataset:**  
shape\_net\_core\_uniform\_samples\_2048  
([https://github.com/optas/latent\\_3d\\_points](https://github.com/optas/latent_3d_points))
- **Dataset size:** 1.32GB point cloud file
- **Dataset file extend:** .ply



- **Train Autoencoder:** 14 model

5120\_out\_.png

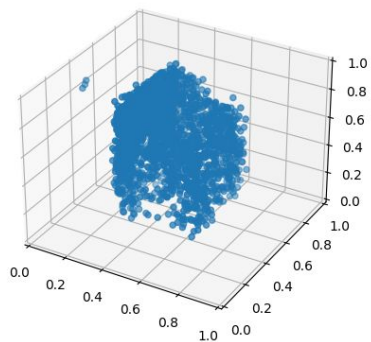
```
[pha0017@argexpr3 RL-GAN]$ ls models/autoencoder/2022-08-06\ 15\19\12.904709/models/  
0_ae_.pt 11_ae_.pt 13_ae_.pt 1_ae_.pt 3_ae_.pt 5_ae_.pt 7_ae_.pt 9_ae_.pt  
10_ae_.pt 12_ae_.pt 14_ae_.pt 2_ae_.pt 4_ae_.pt 6_ae_.pt 8_ae_.pt  
[pha0017@argexpr3 RL-GAN]$ |
```



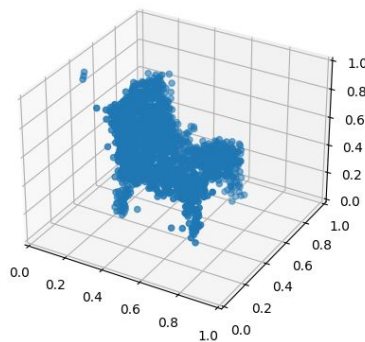
Project Point Cloud Shape Completion



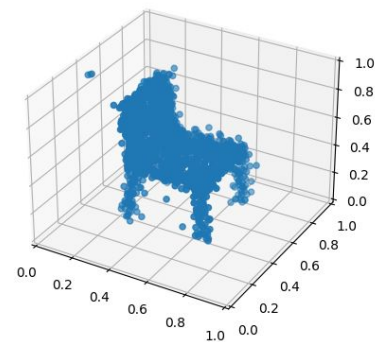
- Train GAN: 980 model
  - Using AE model: 14\_ae.pt



15\_1\_out.png

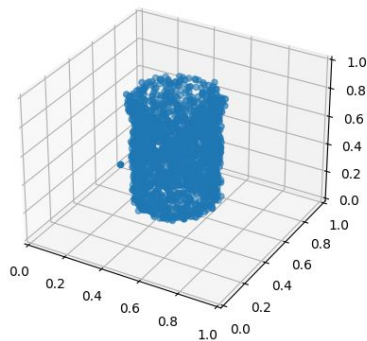


275\_4\_out.png

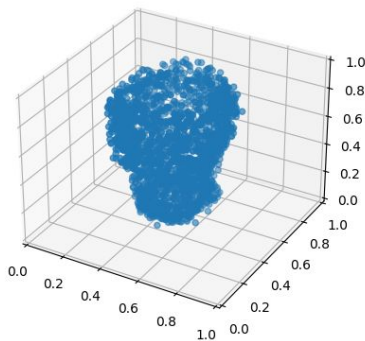


955\_0\_out.png

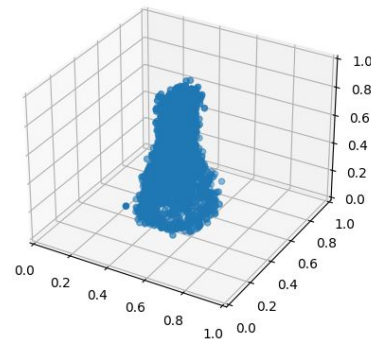
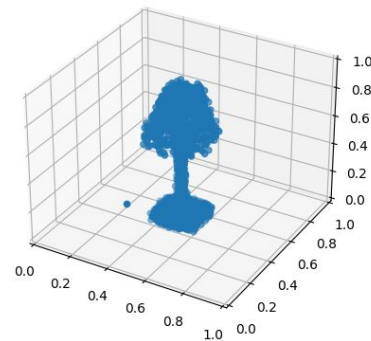
- **Train RL-GAN-Net: 315,000 model**
  - Using AE model: 14\_ae.pt
  - Using GAN model: 980\_gen.pt and 980\_disc.pt



3002\_in.png



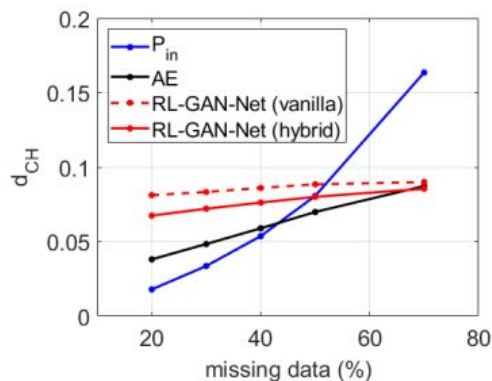
3002\_out.png



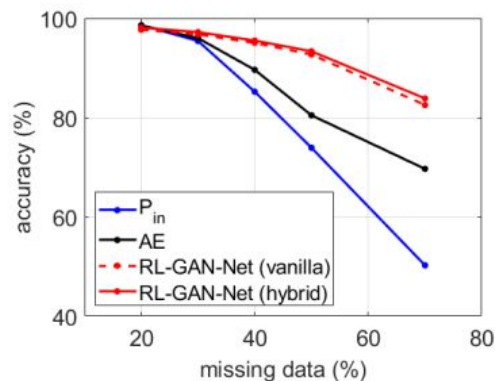
403003.png

Project Point Cloud Shape Completion

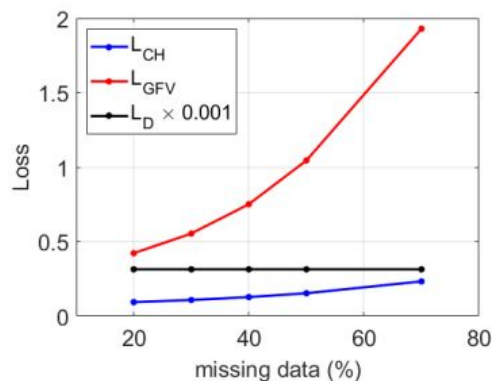
# Performance



(a) Chamfer distance to GT



(b) Classification accuracy [34]



(c) Loss terms

**Figure 5: Performance analysis.** We compare the two versions of our algorithms against the original input and the AE in terms of (a) the Chamfer distance (the lower the better) and (b) the performance gain for shape classification (the higher the better). (c) We also analyze the losses of RL-GAN-Net with different amount of missing data.

# Ref

- <https://github.com/iSarmad/RL-GAN-Net>
- [https://github.com/apoorvkhattar/RL-Project-2019\(update\)](https://github.com/apoorvkhattar/RL-Project-2019(update))
- Muhammad Sarmad, Hyunjoo Jenny Lee, Young Min Kim, RL-GAN-Net: A Reinforcement Learning Agent Controlled GAN Network for Real-Time Point Cloud Shape Completion. <https://arxiv.org/abs/1904.12304>
- [https://github.com/optas/latent\\_3d\\_points](https://github.com/optas/latent_3d_points)
- Panos Achlioptas, Olga Diamanti, Ioannis Mitliagkas, Leonidas Guibas, Learning Representations and Generative Models for 3D Point Clouds. <https://arxiv.org/abs/1707.02392>
- <https://github.com/sfujim/TD3>
- Scott Fujimoto, Herke van Hoof, David Meger, Addressing Function Approximation Error in Actor-Critic Methods. <https://arxiv.org/abs/1802.09477>
- <https://viblo.asia/p/gan-series-1-co-ban-ve-gan-trong-deep-learning-bWrZnE4YKxw>

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