# Fast Point Cloud Sampling Network

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**Abstract**

The increasing number of points in 3D point clouds has brought great challenges for subsequent algorithm efficiencies. Down-sampling algorithms are adopted to simplify the data and accelerate the computation.

## 1 Introduction

Existing works [5] - [2] often use random sampling and the farthest point sampling(FPS) to down-sample the point clouds.

The differences between our work and former learning-based works are presented in Fig 1.

The discrepancy between progress-net and our method is presented in Fig 1(b) and 1(c).

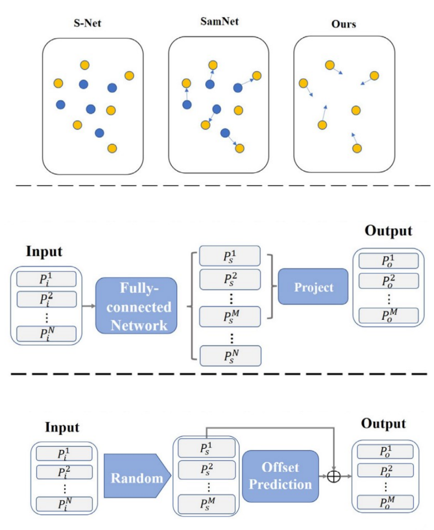


Figure 1:(a) shows the differences between learning-based sampling strategies, while (b) and (c) present the discrepancy between progress-net and our method in multiresolution sampling

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Our contributions can be summarized as:

- We propose a novel learning-based point cloud sampling framework named fast sampling network (FPN) by driving existing randomly sampled points to better positions;
- We introduce a hybrid training strategy to help FPN adapt to different sampling resolutions by randomly introducing selecting the resolution of initial points during training;

# 2 Methodology

## 2.1 *Basic pipeline*

The basic pipeline of FPN is presented in Fig 2 We aggregate global features from the input points with a set of multilevel perceptions (MLPs) and Max Pooling following PointNet [4].

The achievement of HTS is presented as Algorithm 1.

## 2.2 *Loss fuction*

The range constraint can be presented as

$$L_{rc} = \frac{1}{N}\sum ||S_o - S_i||_2, \tag{1}$$

For reconstruction related tasks, it may be Chamfer Distance or Earth Mover Distance [3] defined as

$$\begin{aligned} L_{task} &= L_{CD}(S_1, S_2) \\ &= \frac{1}{2}\left(\frac{1}{|S_1|}\sum_{x\in S_1}\min_{y\in S_2}||x-y||_2 + \frac{1}{|S_2|}\sum_{x\in S_2}\min_{y\in S_1}||x-y||_2\right), \end{aligned} \tag{2}$$

or

$$L_{task} = L_{EMD}(S_1, S_2) = \min_{\phi:S_1\rightarrow S_2}\frac{1}{|S_1|}\sum_{x\in S_1}||x-\phi(x)||_2, \tag{3}$$

where $S_1$ and $S_2$ are input and output. $\phi$ is a bijection from $S_1$ to $S_2$.

# 3 Experiments

## 3.1 *Dataset and implementation details*

**Table 1**

The number of neurons in networks. $f_1$ , $f_2$ , $f_3$ are modules in Fig 2.

| | $f_1$ | $f_2$ | $f_3$ |
|---|---|---|---|
| MLPs | (128,256,256) | (128,256,256) | (128,128,3) |

**Table 2**

The comparison on optimal clustering.

| Center | iterations | 1 | 10 | 100 |
|---|---|---|---|---|
| 16 | FPS | 2.43 | 2.00 | 1.98 |
| | Ours | **2.16** | **1.98** | **1.96** |
| 32 | FPS | 1.20 | 1.02 | 1.00 |
| | Ours | **1.11** | **1.00** | **1.00** |

The hyper-parameter $\lambda$ is tuned on the validation split of ShapeNet. Detailed network structures are shown in Table 3.1.

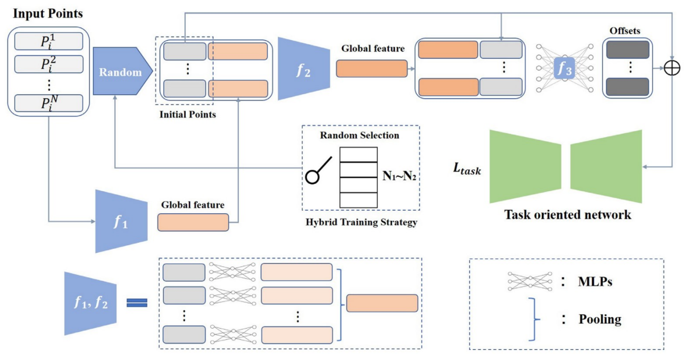


Figure 2: The whole pipeline of FPN. The + denotes element-wised addition. $f_1$ and $f_2$ aggregate features by MultiLayer Perceptrons(MLPs) and pooling, while $f_3$ is a group of MLPs to predict offsets from coordinates and features. The task network is corresponding to the specific task, such as point cloud recognition and reconstruction. $L_{task}$ is the loss constrained the task network

### 3.2 *Discussion about clustering*

Except down-stream tasks such as reconstruction or recognition, down-sampled points can also be adopted as the initial clustering centers. [1]

The results are presented in Table 3.1.

**Algorithm 1** Training with Hybrid Training Strategy

**Input:** data $X$ the number of iterations $iter$, the number of resolutions $m$;
$prob_1$,$prob_2$,...,$prob_m$ $= \frac{1}{m},\frac{1}{m},...,\frac{1}{m}$;
**for** $i = 1$ to $iter$ **do**
  Select the resolution $r$ according to $prob_1$,...,$prob_m$;
  Train FPN by descending gradient: $\delta_{\theta_{FPN}} L_{loss}(Y_{X,r})$
**end for**

### 3.3 *Ablation study*

**The influence of range constraint.** Note that this is only conducted to observe the influence of range constraint weight $\lambda$ on sampling performances instead of the tuning of $\lambda$, which is chosen according to the val set introduced in Section 3.2.

# Data availability

Data will be made available on request

# Acknowledgement

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