APSNet: Attention Based Point Cloud Sampling

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Introduction

This paper introduces APSNet, an attention-based autoregressive network for task-oriented 3D point clouds sampling, which aims to sample a subset of points that are tailored specifically to a downstream task of interest. APSNet employs a sequential autoregressive generation with a novel LSTM-based sequential model for sampling. Depending on the availability of labeled training data, APSNet can be trained in supervised learning or self-supervised learning via knowledge distillation. We also present a joint training of APSNet, yielding a single compact model that can generate arbitrary length of samples with prominent performances. Extensive experiments demonstrate the superior performance of APSNet against state-of-the-arts in various downstream tasks, including 3D point cloud classification, reconstruction, and registration.

Method

Given original point cloud \( P \), thegoal of APSNet is to generate a point cloud \( Q = f_0(P) \) to maximize the predictive performance of task network \( T \). The parameters of APSNet, \( \theta \), are optimized by minimizing a task loss and a sampling loss jointly as

\[
\min_{\theta} L_{\text{task}}(T(Q), y) + \lambda L_{\text{sample}}(Q, P)
\]

The sampling loss \( L_{\text{sample}} \) encourages the sampled points in \( Q \) to be close to those of \( P \) and also have a maximal coverage w.r.t. \( P \).

- **Sampling loss**
  \[
  L_{\text{sample}}(Q, P) = L_{\text{loss}}(Q, P) + \beta L_{\text{inl}}(Q, P) + (\gamma + \delta) L_{\text{out}}(Q, P)
  \]

- **Average nearest neighbor loss**
  \[
  L_{\text{ani}(S_1, S_2)} = \frac{1}{|S_1||S_2|} \sum_{s_1 \in S_1} \sum_{s_2 \in S_2} \min_{s_1 \neq s_2} ||s_1 - s_2||_2
  \]

- **Maximal nearest neighbor loss**
  \[
  L_{\text{man}(S_1, S_2)} = \max_{s_1 \in S_1} \min_{s_2 \in S_2} ||s_1 - s_2||_2
  \]

![Fig. 1 Overview of APSNet. APSNet first extracts features with a simplified PointNet that preserves the geometric information of a point cloud. Then, an LSTM with attention mechanism is used to capture the relationship among points and select the most informative point sequentially. Finally, the sampled point cloud is fed to a task network for prediction. The whole pipeline is optimized by minimizing a task loss and a sampling loss jointly.](https://example.com)

- **Self-supervised Training with Knowledge Distillation**
  The task network \( T \) is the teacher model, and APSNet is the student model and use the soft predictions of \( T \) as the targets to train APSNet.

- **Joint Training**
  Given the autoregressive model of our method, APSNet can generate arbitrary length of samples from a single mode. We can train one APSNet with different sample sizes by

\[
L_{\text{joint}} = \sum_{c \in C} L_{\text{task}}(T(Q), y) + \lambda L_{\text{sample}}(Q, P)
\]

where \( C \) is a set of sample sizes of interest.

3. Inference Time

<table>
<thead>
<tr>
<th>m</th>
<th>SampleNet-G</th>
<th>SampleNet-M</th>
<th>SampleNet-G*</th>
<th>SampleNet-M*</th>
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<tbody>
<tr>
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<td>7.63</td>
<td>13.85</td>
<td>6.78</td>
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<td>128</td>
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<td>256</td>
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<td>13.94</td>
<td>6.80</td>
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<tr>
<td>512</td>
<td>7.94</td>
<td>13.96</td>
<td>6.81</td>
<td>13.72</td>
</tr>
</tbody>
</table>

Classification accuracies with different sample sizes m on ModelNet40.

2. Reconstruction

The normalized reconstruction errors with different sample sizes m on the ShapeNet Core55 dataset.

![Fig. 2 Visualization of sampled points and reconstructed point clouds. APSNet focuses more on the outline of the airplane without losing details, which are critical for the reconstruction](https://example.com)

**Experimental Results**

1. Classification

<table>
<thead>
<tr>
<th>m</th>
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<th>FPS</th>
<th>SampleNet-G</th>
<th>SampleNet-M</th>
<th>SampleNet-G*</th>
<th>SampleNet-M*</th>
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<td>4.27</td>
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<td>1.32</td>
<td>1.27</td>
<td>1.33</td>
<td>1.37</td>
</tr>
</tbody>
</table>

The reconstruction error of different sample sizes m on the ShapeNet Core55 dataset.

**Code: https://github.com/Yangyeee/APSNet**