Learning to Explore using Active Neural SLAM

ICLR-20

Webpage: https://devendrachaplot.github.io/projects/Neural-SLAM
Code: https://github.com/devendrachaplot/Neural-SLAM

Devendra Singh Chaplot
Dhiraj Gandhi
Saurabh Gupta
Abhinav Gupta
Ruslan Salakhutdinov
Exploration
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Exploration

• How to efficiently explore an unseen environment?
  • Memory/Mapping: Where have you been?
  • State/Pose Estimation: Where are you now?
  • Planning: Where do you need to go?
Exploration

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• Limitations of end-to-end RL:
  • High sample complexity
  • Ineffective in large environments
Exploration

• How to efficiently explore an unseen environment?
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• Limitations of end-to-end RL:
  • High sample complexity
  • Ineffective in large environments

• Our solution: Active Neural SLAM
  • Structured spatial representations
  • Hierarchical policies
  • Analytical planners
Active Neural SLAM: Overview
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Sensor Pose Reading ($x'_t$)
Observation ($s_t$)

Neural SLAM ($f_{SLAM}$)

Pose Estimate ($\hat{x}_t$)
Map ($m_t$)

Global Policy ($\pi_G$)

Long-term goal ($g^t$)
Active Neural SLAM: Overview

Sensor Pose Reading ($x_t'$)

Observation ($s_t$)

Neural SLAM ($f_{SLAM}$)

Pose Estimate ($\hat{x}_t$)

Global Policy ($\pi_G$)

Long-term goal ($g_t^l$)

Map ($m_t$)

Short-term goal ($g_t^s$)

$f_{Plan}$
Active Neural SLAM: Overview

Sensor Pose Reading ($x_t'$)

Observation ($s_t$)

Action ($a_t$)

Neural SLAM ($f_{SLAM}$)

Local Policy ($\pi_L$)

Pose Estimate ($\hat{x}_t$)

Global Policy ($\pi_G$)

Map ($m_t$)

Short-term goal ($g_t'$)

Long-term goal ($g'_t$)

Map ($m_t$)

$f_{Plan}$
Neural SLAM Module

- Conv-Deconv Neural Network
- Trained with supervised learning
- Learns explicit structured map and pose representations
Global Policy

- Convolutional Neural Network
- Trained with reinforcement learning
- Operates at a course time-scale
Local Policy

- Convolutional Neural Network
- Trained with imitation learning
- Operates at a fine time-scale
Neural SLAM Module
Neural SLAM Module

Sensor Pose Reading \((x'_{t-1})\)

Observation \((s_{t-1})\)

Sensor Pose Reading \((x'_t)\)

Observation \((s_t)\)
Neural SLAM Module

Sensor Pose Reading \( (x'_{t-1}) \)

Observation \( (s_{t-1}) \)

Mapper \( (f_{Map}) \)

Sensor Pose Reading \( (x'_t) \)

Observation \( (s_t) \)

Mapper \( (f_{Map}) \)
Neural SLAM Module

Sensor Pose Reading ($x'_{t-1}$) → Mapper ($f_{Map}$) → Egocentric Proj. ($p_{t-1}^{ego}$)

Observation ($s_{t-1}$)

Sensor Pose Reading ($x'_t$) → Mapper ($f_{Map}$) → Egocentric Proj. ($p_{t}^{ego}$)

Observation ($s_t$)
Neural SLAM Module

Sensor Pose Reading \( (x_t') \)

Observation \( (s_t) \)

Sensor Pose Reading \( (x_t') \)

Observation \( (s_t-1) \)

Mapper \( (f_{map}) \)

Relative Pose Change \( (dx) \)

Mapper \( (f_{map}) \)

Egocentric Proj. \( (p_{ego}^{ego}) \)

Egocentric Proj. \( (p_{ego}^{ego}) \)
Neural SLAM Module

Sensor Pose Reading ($x'_t$)

Observation ($s_{t-1}$)

Mapper ($f_{Map}$)

Relative Pose Change ($dx$)

Sensor Pose Reading ($x'_t$)

Observation ($s_t$)

Mapper ($f_{Map}$)

Egocentric Proj. ($P_{t-1}^{ego}$)

Egocentric Proj. ($P_t^{ego}$)

ST
Neural SLAM Module

Sensor Pose Reading ($x'_t$)

Observation ($s_{t-1}$)

Mapper ($f_{Map}$)

Relative Pose Change ($dx$)

ST

Sensor Pose Reading ($x'_t$)

Observation ($s_t$)

Mapper ($f_{Map}$)

Egocentric Proj. ($p_{t-1}^{ego}$)

Egocentric Proj. ($p_t^{ego}$)
Neural SLAM Module

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Relative Pose Change ($dx$)

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Egocentric Proj. ($p_t^{ego}$)

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Pose Estimate ($\hat{x}_{t-1}$)

Pose Estimator ($f_{PE}$)

Observation ($s_t$)

Sensor Pose Reading ($x'_t$)
Neural SLAM Module

Sensor Pose Reading ($x_{t-1}$)
Observation ($s_{t-1}$)
Mapper ($f_{Map}$) → Relative Pose Change ($d_x$)
Mapper ($f_{Map}$) → Egocentric Proj. ($p_t^{ego}$)
Pose Estimate ($\hat{x}_t$)

Observation ($s_t$)
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Pose Estimate ($\hat{x}_t$)

Pose Estimate ($\hat{x}_{t-1}$)
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Neural SLAM Module

Sensor Pose Reading ($x_t^r$)

Observation ($s_t$)

Sensor Pose Reading ($x_{t-1}^r$)

Observation ($s_{t-1}$)

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Pose Estimator ($f_{PE}$)

Pose Estimate ($\hat{x}_{t}$)

ST

Pose Estimate ($\hat{x}_{t-1}$)

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ST

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ST

Channel Pool

Map ($m_{t-1}$)

Map ($m_t$)
Neural SLAM Module

Sensor Pose Reading ($x_{t-1}'$)

Observation ($s_{t-1}$)

Sensor Pose Reading ($x_t'$)

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Channel Pool

Geocentric Proj. ($p_t^{geo}$)

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Exploration: Task Setup
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Exploration: Task Setup

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- **Objective**: Maximize the explored area
  - A cell is explored when it is known to be traversable
- **Metrics**:
  - **Coverage (m²)** - absolute explored area or coverage
  - % **Coverage** - percentage of the environment explored

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- Fixed episode length of 1000 steps

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- Fixed episode length of 1000 steps
- All methods trained for 10 million frames

Demo Video: Exploration

Observation

Predicated Map and Pose

https://youtu.be/tlyz68j_jvE
Exploration Results
Exploration Results

% Coverage

RL + 3LConv [1]
RL + Res18
RL + Res18 + AuxDepth [2]
RL + Res18 + ProjDepth [3]
Active Neural SLAM

Exploration Results

% Coverage

Gibson

- RL + 3LConv [1] 73.7
- RL + Res18 74.7
- RL + Res18 + ProjDepth [3] 78.9
- Active Neural SLAM 94.8

Coverage ($m^2$)

- 22.838
- 23.188
- 24.467
- 24.863
- 32.701

Exploration Results

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Exploration Results

Domain Generalization

**MP3D**

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<td>33.2</td>
<td>47.758</td>
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<tr>
<td>RL + Res18</td>
<td>34.1</td>
<td>49.175</td>
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<tr>
<td>RL + Res18 + ProjDepth [3]</td>
<td>37.8</td>
<td>54.775</td>
</tr>
<tr>
<td>Active Neural SLAM</td>
<td>52.1</td>
<td>73.281</td>
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# Ablation

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<tr>
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<th>Gibson Val Overall</th>
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<tr>
<td></td>
<td>% Cov.</td>
<td>Cov. (m²)</td>
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<tr>
<td>ANS w/o Local Policy + Det. Planner</td>
<td>0.941</td>
<td>32.188</td>
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<td>0.925</td>
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Replace Local Policy by Analytical Deterministic Policy
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Replace Local Policy by
Analytical Deterministic Policy

Replace Global Policy by
Frontier-based Exploration
## Ablation

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Local Policy does not improve much over deterministic policy.

Replace Local Policy by Analytical Deterministic Policy.
Replace Global Policy by Frontier-based Exploration.
# Ablation

Local Policy does not improve much over deterministic policy

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Replace Local Policy by Analytical Deterministic Policy
Replace Global Policy by Frontier-based Exploration

Global Policy and Pose Estimation mostly help in Large Estimation
Pointgoal: Task Transfer
Pointgoal: Task Transfer

• Objective: Navigate to goal coordinates
Pointgoal: Task Transfer

- Objective: Navigate to goal coordinates
- Metric: Success weighted by inverse Path Length (SPL)

\[
\frac{1}{N} \sum_{i=1}^{N} \text{Success} \times \frac{\text{ShortestPathLength}}{\text{PathLength}}
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Pointgoal: Task Transfer

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\frac{1}{N} \sum_{i=1}^{N} \text{Success} \times \frac{\text{ShortestPathLength}}{\text{PathLength}}
\]

- Global Policy -> always gives the pointgoal as the long-term goal
Harder Datasets

- **Hard-GEDR**
  - Higher Geodesic to Euclidean distance ratio (GEDR)
  - Avg GEDR 2.5 vs 1.37, minimum GEDR is 2

- **Hard-Dist**
  - Higher Geodesic distance
  - Avg Dist 13.5m vs 7.0m, minimum Dist is 10m
PointGoal Results
PointGoal Results

PointGoal Results

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<td>IL + Res18</td>
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<td>0.421</td>
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</tr>
<tr>
<td>RL + 3LConv [1]</td>
<td>0.406</td>
<td>0.550</td>
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<tr>
<td>RL + Res18</td>
<td>0.422</td>
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<tr>
<td>RL + Res18 + AuxDepth [2]</td>
<td>0.461</td>
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<td>RL + Res18 + ProjDepth [3]</td>
<td>0.436</td>
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<tr>
<td>IL + Res18</td>
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<tr>
<td>IL + CMP [4]</td>
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<tr>
<td>Active Neural SLAM (ANS)</td>
<td>0.848</td>
<td>0.951</td>
</tr>
<tr>
<td>Ours</td>
<td>0.846</td>
<td>0.950</td>
</tr>
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</table>

## PointGoal Results

<table>
<thead>
<tr>
<th>Method</th>
<th>SPL</th>
<th>Success</th>
</tr>
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<tbody>
<tr>
<td>Random</td>
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<td>RL +盲</td>
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<tr>
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<tr>
<td>RL + Res18 + AuxDepth [2]</td>
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<tr>
<td>RL + Res18 + ProjDepth [3]</td>
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<tr>
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PointGoal Results

<table>
<thead>
<tr>
<th>Method</th>
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<tbody>
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</tr>
<tr>
<td>Reinforcement Learning</td>
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<td></td>
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<tr>
<td>RL + Blind</td>
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<td>0.008</td>
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<td>RL + 3LConv [1]</td>
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<tr>
<td>RL + Res18</td>
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<tr>
<td>RL + Res18 + AuxDepth [2]</td>
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<td>Imitation Learning</td>
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<tr>
<td>IL + CMP [4]</td>
<td>0.318</td>
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<tr>
<td>Active Neural SLAM (ANS)</td>
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<td>0.662</td>
</tr>
<tr>
<td>Ours</td>
<td>0.532</td>
<td>0.665</td>
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PointGoal Results

<table>
<thead>
<tr>
<th>Method</th>
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<th>Success</th>
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<tr>
<td>RL + 3LConv [1]</td>
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<tr>
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<td>0.134</td>
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<tr>
<td>Imitation Learning:</td>
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<td></td>
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<tr>
<td>IL + Res18</td>
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<tr>
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<td>Ours: Ours</td>
<td>0.49</td>
<td>0.588</td>
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Results

Gibson

Domain Generalization (Matterport 3D)

Goal Generalization (Harder goals)

Exploration

https://youtu.be/tlyz68j_jvE

https://youtu.be/T2yfqrxP0Gg

Task Generalization

Pointgoal

https://youtu.be/4a3Mt7lmSK8

https://youtu.be/_k9r19qCcsk

https://youtu.be/G6kc_GtltR8
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Winner of CVPR 2019 Habitat Challenge

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team</th>
<th>SPL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Active Neural SLAM (Arnold)</td>
<td>0.805</td>
</tr>
<tr>
<td>1</td>
<td>Mid-level-Features</td>
<td>0.800</td>
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<tr>
<td>3</td>
<td>CHROMA</td>
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<tr>
<td>5</td>
<td>MTank</td>
<td>0.260</td>
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</table>

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<thead>
<tr>
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</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Active Neural SLAM (Arnold)</td>
<td>0.948</td>
</tr>
<tr>
<td>2</td>
<td>Pansy</td>
<td>0.927</td>
</tr>
<tr>
<td>3</td>
<td>Titardrew</td>
<td>0.868</td>
</tr>
<tr>
<td>4</td>
<td>Hiccup</td>
<td>0.846</td>
</tr>
<tr>
<td>5</td>
<td>CHROMA</td>
<td>0.843</td>
</tr>
</tbody>
</table>
## Winner of CVPR 2019 Habitat Challenge

### RGB Leaderboard

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team</th>
<th>SPL</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
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<td>0.805</td>
</tr>
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<td>2</td>
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<td>0.927</td>
</tr>
<tr>
<td>3</td>
<td>Titardrew</td>
<td>0.866</td>
</tr>
<tr>
<td>4</td>
<td>ARF-RL</td>
<td>0.846</td>
</tr>
<tr>
<td>5</td>
<td>MTank</td>
<td>0.260</td>
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</table>

### RGBD Leaderboard

<table>
<thead>
<tr>
<th>Rank</th>
<th>Team</th>
<th>SPL</th>
</tr>
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<tbody>
<tr>
<td>1</td>
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<tr>
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<td>Pansy</td>
<td>0.927</td>
</tr>
<tr>
<td>3</td>
<td>Titardrew</td>
<td>0.866</td>
</tr>
<tr>
<td>4</td>
<td>Hiccup</td>
<td>0.846</td>
</tr>
<tr>
<td>5</td>
<td>CHROMA</td>
<td>0.843</td>
</tr>
</tbody>
</table>
Sim-to-Real Transfer

Observation

Third-person view

Predicted Map and Pose

https://youtu.be/afqbn3gpeiA
Learning to Explore using Active Neural SLAM

Webpage: [https://devendrachaplot.github.io/projects/Neural-SLAM](https://devendrachaplot.github.io/projects/Neural-SLAM)

Code: [https://github.com/devendrachaplot/Neural-SLAM](https://github.com/devendrachaplot/Neural-SLAM)

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Thank you

Devendra Singh Chaplot


Email: chaplot@cs.cmu.edu

Twitter: @dchaplot