Learning robot navigation with differentiable projective and topological memory

Christian Wolf
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Seminar @ Onera
Who am I?

Christian Wolf, Associate Professor, HDR
Chair in Research and Teaching in Artificial Intelligence at INSA-Lyon,
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Learning vision & robotics

Gesture recognition

Pose estimation

Activity Recognition

Robot Perception and Navigation

H-C Interaction

Physics
Learning to navigate in 3D environments

Office space

Homes

Exposition centers

Hospitals
The team

Edward Beeching  Jilles Dibangoye  Olivier Simonin  Christian Wolf

[Images of team members]
Find my keys!

Can we learn a spatial representation which is richer than navigational space?

Can we learn it from reward alone?
CITI lab agent
Learning high-level reasoning

Find and return
- Find an object in a maze and then returning to the starting point
- Sparse rewards:
  - 0.5 for finding the object
  - 0.5 for returning to the starting point

Ordered K-item
- Collect k items in a fixed order
- Sparse rewards:
  - 0.5 for each object collected

[Beeching et al., ICPR 2020]
Scenarios: Ordered K-item

- Collect K items in a specific order
- Tests: Vision & memory
Generalization to unseen mazes

How many training configurations are required to generalize to unseen test configurations?
Generalization to unseen mazes
K-item scenario: recurrent agent (A3C)

Training scenarios

Testing scenarios
Learning Reasoning, Memory and Behavior

AI Chair “Remember”

Constraints + Structure:
Geometry, Topology, Semantics, Stability

Memory
Semantic + spatial representation

Behavior / Control

Learning, querying, attending

Agents

Learning with different losses:
Reward, (self)-supervision, Intrinsic motivation, curiosity

Observations

π

ν
The unstructured recurrent baseline
Spatial maps in robotics

Metric map
(=2D or 3D Grid)

Topological map
(=Graph)

Beeching, Dibangoye, Simonin, Wolf,
*EgoMap: Projective mapping and structured egocentric memory for Deep RL*,
ECML-PKKD 2020

Beeching, Dibangoye, Simonin, Wolf,
*Learning to plan with uncertain topological maps*,
ECCV 2020
Projective mapping
Learning agent control/behavior

\[
\begin{align*}
\text{Perception module} & \quad \pi \quad v \\
\text{Controller} & \quad h_{t-1} \\
\text{Inverse projective mapping} & \quad \text{Differentiable affine transform} \\
\text{Perception module} & \quad h_t \\
\text{Controller} & \quad h_{t+1} \\
\frac{dE}{dX} &
\end{align*}
\]
A single forward pass

1. Transform the map to the agent’s egocentric frame of reference

\[ \hat{M}_t = \text{Affine}(M_{t-1}, dx_t, dy_t, d\phi_t) \]

2. Update the map to include new observations

\[ \tilde{M}_t = \text{InverseProject}(s_t, D_t) \quad M'_t = \text{Combine}(\hat{M}_t, \tilde{M}_t) \]

3. Perform a global read and attention based read,

\[ r_t = \text{Read}(M'_t) \quad c_t = \text{Context}(M'_t, s_t, r_t) \]
Occupancy Grid vs. Egomap

[Rummelhard, Negre, Laugier, 2015]

[Beeching, Dibangoye, Simonin, Wolf, ECML-PKDD 2020]
Querying spatial memory

The network learns to query for specific content

Ease localization with coordinate planes
Querying spatial memory

The network learns to query for specific content
6 item scenario: time-step 005

Projective mapping of blue object

EgoMap: Query position

EgoMap: Attention

Object features retained in map

EgoMap: 3 Largest principal components
6 item scenario: time-step 105

EgoMap: Query position

EgoMap: Attention

Object features retained in map

EgoMap: 3 Largest principal components
6 item scenario: time-step 108

EgoMap: Attention

EgoMap: Query position

EgoMap: 3 Largest principal components

Collection of object n-1 triggers attention to object n
6 item scenario: time-step 134

EgoMap: Query position

EgoMap: Attention

EgoMap: 3
Largest
principal
components
6 item scenario: time-step 140

When the object is not occluded, the agent does not attend to it.
Results

![Graph showing performance over time for different methods.](image)

- **Baseline**
- **EgoMap**
- **Neural Map**

*Upper bound on optimal Policy*
## Quantitative results

<table>
<thead>
<tr>
<th>Agent</th>
<th>4 item</th>
<th>6 item</th>
<th>Find and Return</th>
<th>Labyrinth</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Train</td>
<td>Test</td>
<td>Train</td>
<td>Test</td>
</tr>
<tr>
<td>Random</td>
<td>-0.179</td>
<td>-0.206</td>
<td>-0.21</td>
<td>-0.21</td>
</tr>
<tr>
<td>Baseline</td>
<td>2.341 ± 0.026</td>
<td>2.266 ± 0.035</td>
<td>2.855 ± 0.164</td>
<td>2.545 ± 0.226</td>
</tr>
<tr>
<td>Neural Map</td>
<td>2.339 ± 0.038</td>
<td>2.223 ± 0.040</td>
<td>2.750 ± 0.062</td>
<td>2.465 ± 0.034</td>
</tr>
<tr>
<td>EgoMap</td>
<td>2.398 ± 0.014</td>
<td>2.291 ± 0.021</td>
<td>3.214 ± 0.007</td>
<td>2.801 ± 0.048</td>
</tr>
<tr>
<td>Optimum</td>
<td>2.5</td>
<td>2.5</td>
<td>3.5</td>
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</tr>
</tbody>
</table>

Mark: Mapping objects required

Learner: Not required
Results: ablation study

<table>
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<th>Ablation</th>
<th>Train</th>
<th>Test</th>
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<tr>
<td>Baseline</td>
<td>0.668 ± 0.028</td>
<td>0.662 ± 0.036</td>
</tr>
<tr>
<td>No global read</td>
<td>0.787 ± 0.007</td>
<td>0.771 ± 0.029</td>
</tr>
<tr>
<td>No query</td>
<td>0.838 ± 0.003</td>
<td>0.811 ± 0.013</td>
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<tr>
<td>No query temperature</td>
<td>0.845 ± 0.014</td>
<td>0.815 ± 0.019</td>
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<tr>
<td>No query position</td>
<td>0.839 ± 0.007</td>
<td>0.814 ± 0.008</td>
</tr>
<tr>
<td>Cosine query</td>
<td>0.847 ± 0.011</td>
<td>0.814 ± 0.017</td>
</tr>
<tr>
<td><strong>L1 query</strong></td>
<td><strong>0.851 ± 0.014</strong></td>
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Quantitative analysis: Ablations

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<th>Noise std. Average return</th>
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<tr>
<td>0.00</td>
<td>0.702 ± 0.026</td>
<td></td>
</tr>
<tr>
<td>0.02</td>
<td>0.686 ± 0.027</td>
<td></td>
</tr>
<tr>
<td>0.04</td>
<td>0.669 ± 0.031</td>
<td></td>
</tr>
<tr>
<td>0.06</td>
<td>0.623 ± 0.018</td>
<td></td>
</tr>
<tr>
<td>0.08</td>
<td>0.585 ± 0.017</td>
<td></td>
</tr>
<tr>
<td>0.10</td>
<td>0.568 ± 0.023</td>
<td></td>
</tr>
<tr>
<td>0.12</td>
<td>0.575 ± 0.020</td>
<td></td>
</tr>
<tr>
<td>0.14</td>
<td>0.578 ± 0.023</td>
<td></td>
</tr>
<tr>
<td>0.16</td>
<td>0.546 ± 0.017</td>
<td></td>
</tr>
<tr>
<td>0.20</td>
<td>0.537 ± 0.031</td>
<td></td>
</tr>
<tr>
<td>Baseline</td>
<td>0.527 ± 0.047</td>
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Spatial maps in robotics

Metric map (=2D or 3D Grid)

Beeching, Dibangoye, Simonin, Wolf,
_EgoMap: Projective mapping and structured egocentric memory for Deep RL_,
ECML-PKKD 2020

Topological map (=Graph)

Beeching, Dibangoye, Simonin, Wolf,
_Learning to plan with uncertain topological maps_,
ECCV 2020
Uncertain topological maps

Ground truth
Uncertain topological maps

Ground truth
Uncertain topological maps

Ground truth

CNN

Node features
Uncertain topological maps

Ground truth

Uncertain graph

False negative

False positive
Uncertain topological maps

Classical planning:
- Binary connectivity
- Cannot exploit visual information
Uncertain topological maps

Classical planning:
• Binary connectivity
• Cannot exploit visual information

Neural planning:
• Exploits uncertain connectivity
• Uses visual features
• Uses neighbor information
Shortest path problems: Dijkstra’s algorithm
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Shortest path problems: Dijkstra’s algorithm

Update of the bound
Shortest path problems: Dijkstra’s algorithm
Shortest path problems: Dijkstra’s algorithm
Planning as classification
with Graph Neural Networks

Supervision with Result of Dijkstra’s algorithm

\[ L \]
## Results: Neural planner

(a) Uncertain graphs

<table>
<thead>
<tr>
<th>Method</th>
<th>Acc</th>
<th>H-SPL</th>
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<tbody>
<tr>
<td>Symbolic (threshold)</td>
<td>0.114</td>
<td>0.184</td>
</tr>
<tr>
<td>Symbolic (custom cost)</td>
<td>0.115</td>
<td>0.269</td>
</tr>
<tr>
<td>Neural (w/o visual)</td>
<td>0.251</td>
<td>0.468</td>
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<tr>
<td>Neural (w visual)</td>
<td><strong>0.262</strong></td>
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(b) Ground truth graphs

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<tr>
<td>Symbolic (GT)</td>
<td><strong>1.00</strong></td>
<td><strong>1.00</strong></td>
</tr>
<tr>
<td>Neural planner (GT)</td>
<td>0.921</td>
<td>0.983</td>
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We can beat optimal algorithms ... 
... by cheating ... data is King!
Results: Neural planner

(a) Uncertain graphs

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(b) Ground truth graphs

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Ablation: Visual features

![Graph showing the relationship between dataset size and validation accuracy or H-SPL for different feature sets. The blue line represents 'Connection probs.', while the orange line represents 'Probs. and visual features.' The graphs compare performance across different dataset sizes.](image-url)
Ablation: GRU for min operation
Hierarchical planning

- **Environment**
  - Observed image $\pi, v$

- **Inner loop**
  - Position estimate
  - Local policy

- **Outer loop**
  - Next node
  - Graph planner

- **Uncertain topological map + visual representation**
  - $\mathbf{x}_i$
Hierarchical planning and control
Hierarchical planning and control
Results: Hierarchical planning and control

<table>
<thead>
<tr>
<th>Method: Planner + Local policy</th>
<th>Success rate</th>
<th>SPL</th>
</tr>
</thead>
<tbody>
<tr>
<td>Graph oracle (optimal point-goals, not comparable)</td>
<td>0.963</td>
<td>0.882</td>
</tr>
<tr>
<td>Random</td>
<td>0.152</td>
<td>0.111</td>
</tr>
<tr>
<td>Recurrent Image-goal agent</td>
<td>0.548</td>
<td>0.248</td>
</tr>
<tr>
<td>Symbolic (threshold)</td>
<td>0.621</td>
<td>0.527</td>
</tr>
<tr>
<td>Symbolic (custom cost)</td>
<td>0.707</td>
<td>0.585</td>
</tr>
<tr>
<td>Neural planner (sampling)</td>
<td>0.966</td>
<td>0.796</td>
</tr>
<tr>
<td>Neural planner (deterministic)</td>
<td><strong>0.983</strong></td>
<td><strong>0.877</strong></td>
</tr>
</tbody>
</table>
Failure Case
Conclusion

- We aim address the problem of planning and control in photorealistic 3D environments

- We imbue neural networks with inductive bias for planning:
  - Projective geometry (metric maps)
  - Graph based planning

- We learn to plan in uncertain environments

- Future work:
  - Dynamic graph creation
  - Sim2real transfer