

A Critical Investigation of Deep Reinforcement Learning for Navigation

Vikas Dhiman^{1*}, Shurjo Banerjee^{1*}, Brent Griffin¹, Jeffrey M Siskind², Jason J Corso¹

¹EECS, University of Michigan, Ann Arbor, MI and ²ECE, Purdue University, West Lafayette, IN
¹{dhiman, shurjo, griffb, jjcorso}@umich.edu, ²qobi@purdue.edu

Abstract

The navigation problem is classically approached in two steps: an *exploration* step, where map-information about the environment is gathered; and an *exploitation* step, where this information is used to navigate efficiently. Deep reinforcement learning (DRL) algorithms, alternatively, approach the problem of navigation in an end-to-end fashion. Inspired by the classical approach, we ask whether DRL algorithms are able to inherently explore, gather and exploit map-information over the course of navigation. We build upon Mirowski *et al.* [2017]’s work and introduce a systematic suite of experiments that vary three parameters: the agent’s starting location, the agent’s target location, and the maze structure. We choose evaluation metrics that explicitly measure the algorithm’s ability to gather and exploit map-information. Our experiments show that when trained and tested on the same maps, the algorithm successfully gathers and exploits map-information. However, when trained and tested on different sets of maps, the algorithm fails to transfer the ability to gather and exploit map-information to unseen maps. Furthermore, we find that when the goal location is randomized and the map is kept static, the algorithm is able to gather and exploit map-information but the exploitation is far from optimal. We open-source our experimental suite in the hopes that it serves as a framework for the comparison of future algorithms and leads to the discovery of robust alternatives to classical navigation methods.

1 Introduction

Navigation remains a fundamental problem in mobile robotics and artificial intelligence [Smith and Cheeseman, 1986; Elfes, 1989]. The problem is classically addressed by separating the task of navigation into two steps: *exploration* and *exploitation*. In the exploration stage, an internal *map-like* representation of the environment is built. In the exploitation stage, this map is used to *plan a path* to a given destination.

*The first two authors contributed equally.

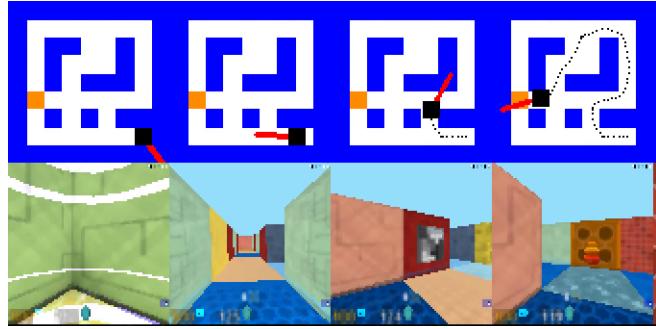


Figure 1: Snapshots of the path taken by an agent navigating a deepmind lab environment. The top row shows the top view of the robot moving through the maze with the goal location marked in orange, the agent marked in black and the agent’s orientation marked in red. The bottom row shows the first person view which is the only input available to the agent besides the previously earned reward.

tion based on some optimality criterion (e.g., shortest path or minimum energy path). Despite enjoying wide success with a variety of environments and sensor types, this classical approach is heavily dependent on the choice of feature-representation and map representation given the environment being navigated.

Recently, end-to-end navigation methods have gained traction, bolstered by advances in Deep Reinforcement Learning (DRL) [Mnih *et al.*, 2016; Silver *et al.*, 2016; Levine *et al.*, 2017; Mirowski *et al.*, 2017; Oh *et al.*, 2016]. In these methods, the manual design of the input features, intermediate map-building and path-planning stages is replaced with the design of a *reward function*, a one-dimensional proxy for the navigation objective. DRL agents then learn intermediate map representations tailored to the maximization of this reward function.

The potential for such simpler formulations of the navigation problem is rich. For example, when the reward function is customized to the finding of destinations within a maze, the resulting trained agents may discover features and map representations that allow for more efficient completion of the navigation task than human-interpretable maps.

Recent works in the field, however, fail to measure the algorithm’s ability to gather and exploit map-information [Zhu *et al.*, 2017; Kulkarni *et al.*, 2016; Jaderberg *et al.*, 2016;

Gupta *et al.*, 2017]. Agents are usually tasked with finding a destination, sometimes in an unseen environment and evaluated on some measure of time taken to find the destination. Though agents may learn to remember map information to find the destination faster as they navigate, the evaluation metrics used by these works do not explicitly separate and measure the agent’s facilities for exploration and exploitation. We believe that such an explicit separation is a necessary step for the formulation of agents that perform well on the meta-task of navigation and can someday provide robust alternatives to classical methods.

Work by Mirowski *et al.* [2017] represents a first step in this direction. Their experimental setup consists of an agent randomly spawned within an environment whose map-structure remains constant throughout training and testing. The agent is tasked with discovering a goal location within the environment. Upon finding the goal, it is rewarded and randomly reinitialized. Episodes consist of fixed time-length intervals. To maximize reward, agents must first find the goal and then repeatedly revisit it during the course of an episode. The task is thus explicitly oriented towards the creation and study of agents that must perform both exploration and exploitation to maximize reward. To measure these effects, the authors report the *Latency-1:>1* metric, the ratio of time taken to first find the goal to the average time taken to revisit the goal.

This work builds upon the experimental setup introduced in their work by further seeking to understand exactly where DRL-based navigation methods succeed and fail across a variety of static and random environments. We train and evaluate the algorithm on problems of increasing difficulty. In the easiest stage, we keep the spawn location, the goal location, and the map constant over the training and testing. To increase the difficulty, we incrementally randomize the spawn location, goal location and map structure until all three variables are random. In the most difficult stage, agents are trained on 1000 random maps and tested on 100 previously unseen maps. In addition to reporting the *Latency-1:>1* metric, we introduce the *Distance-inefficiency* metric, the ratio of distance covered by the agent as compared to the approximate shortest path length to the goal.

In the case where environments are kept static throughout training and testing, we find that agents are able to perform effective exploitation by consistently finding the goals faster post-goal discovery (*Latency-1:>1* is greater than 1), in line with the findings of Mirowski *et al.* [2017]. Furthermore, of these cases where the goals are static, the *Distance-inefficiency* is approximately 1, indicating near-optimal goal discovery; by contrast, cases with randomized goals perform sub-optimally. For the cases where the agents are trained on 1000 maps and tested on 100 unseen maps, we find no evidence that map gathering and exploitation is taking place. To further highlight this, we qualitatively assess the navigational strategies utilized by these agents across simplified *planning maps* that require the agents to make simple binary decisions at junction points. Finally, we compute attention maps to qualitatively analyze the environmental cues utilized by these agents to make decisions at different points in the map.

To summarize, our contribution is two fold. First, we pro-

pose a systematic suite of experiments along with a set evaluation metrics that explicitly evaluate the ability of algorithms to exploit map information. Second, we answer whether a representative DRL algorithm is able to exploit map information under this experimental suite.

2 Related Work

Localization and mapping Localization and mapping for navigation is a classic problem in mobile robotics and sensing. Smith and Cheeseman [1986] introduced the idea of propagating spatial uncertainty for robot localization while mapping, and Elfes [1989] popularized Occupancy Grids. In the three decades since this seminal work, the field has exploded with hundreds of algorithms for many types of sensors (e.g., cameras, laser scanners, sonars and depth sensors). These algorithms vary in the amount of detail they capture in their respective maps. For example, topological maps, like Kuipers [1978], aim to capture as little information as possible while occupancy grid maps such as Elfes [1989], aim to capture metrically accurate maps in resolutions dependent upon the navigation task.

All these approaches require significant hand-tuning for the environment, sensor types, and navigation constraints of the hardware. In contrast, end-to-end navigation algorithms optimize the detail of map storage based on the navigation task at hand. This significant advantage makes end-to-end navigation ripe for exploring.

Deep reinforcement learning DRL gained prominence recently when used by Mnih *et al.* [2013, 2015] to train agents that outperform humans on Atari games; agents that were trained using only the games’ visual output. More recently, DRL has been applied to end-to-end navigation [Oh *et al.*, 2016; Mirowski *et al.*, 2017; Chaplot *et al.*, 2016]. It is common for agents to be trained and tested on the same maps with the only variation being the agent’s initial spawn point and the map’s goal location [Mirowski *et al.*, 2017; Zhu *et al.*, 2017; Kulkarni *et al.*, 2016]. Even when the agents are tested on unseen environments [Mnih *et al.*, 2015; Jaderberg *et al.*, 2016; Gupta *et al.*, 2017], they are evaluated using metrics which only measure the exploration abilities of the agents. By exploration abilities, we mean that the agent is tasked to find a goal location or object in the unseen environment, and the reported metrics are some variation of the time taken to find the goal. On the other hand, a metric for exploitation ability will measure the ability of the agent to find a visited location in the unseen map again.

Oh *et al.* [2016] test their algorithm on random unseen maps, but their agents are trained to choose between multiple potential goal locations based on past observations. The episodes end when the agent collects the goal, so there is no requirement for the algorithm to store map information during exploration. Thus, their agents decide to avoid a goal of a particular color while seeking other colors rather than remembering the path to the goal. Similarly Parisotto and Salakhutdinov [2017] extend Oh *et al.* [2016] to work for long time ranges by indexing the memory with spatial coordinates. Chaplot *et al.* [2016] test their method on unseen maps in the

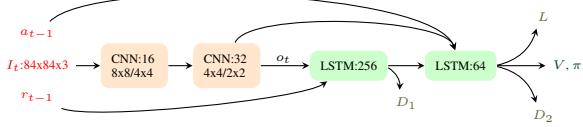


Figure 2: Modified NavA3C+D₁D₂L architecture. The architecture has three inputs: the current image I_t , the previous action a_{t-1} , and the previous reward r_{t-1} . As shown by Mirowski *et al.* [2017], the architecture improves upon vanilla A3C architecture by using auxiliary outputs of loop-closure signal L and predicted depth D_1 and D_2 .

VizDoom environment, but only vary the maps with unseen textures. Thus, their agents are texture invariant, but train and test on maps with the same geometric structure.

In this work, we propose an extension to the study of these methods in a more comprehensive set of experiments to address the question of whether DRL-based agents remember enough information to obviate mapping algorithms or may in fact need to be augmented with mapping for further progress.

3 Environmental Setup

We evaluate the algorithms on a simulated environment. We use the same game engine as Mirowski *et al.* [2017], called Deepmind Lab [Beattie *et al.*, 2016]. The game is setup so that an agent is placed within a randomly generated maze containing a *goal* at a particular location, x_g . On hitting the goal, the agent *re-spawns* within the same maze while the goal location remains unchanged. The maze is scattered with randomly placed smaller apple rewards (+1) to encourage initial explorations and the goal is assigned a reward of $r_g = +10$. The agent is tasked with finding the goal as many times as possible within a fixed amount of time ($T = 1200$ steps for our experiments), re-spawning within the maze, either statically or randomly, each time it reaches the goal. We include a small wall penalty (-0.2) that pushes the agent away from the wall to prevent agents from moving along the walls during initial explorations. At every point the agent must choose between moving forward or backward or rotating left or right. Following Chaplot *et al.* [2016], we use randomly textured walls in our mazes so that the policies learned are texture-independent.

We generate 1100 random maps using recursive depth-first search-based maze generation methods [Aycoc, 2016]. Of the first 1000 maps, 10 are randomly selected for our static-map experiments. For our unseen map experiments, agents are trained on increasing subsets of the first 1000 maps and tested on the remaining 100.

4 Network architecture

Our network architecture is a simplified version of the NavA3C+D₁D₂L model used by Mirowski *et al.* [2017]. A schematic of the architecture is shown in Fig 2. We chose NavA3C+D₁D₂L as a representative DRL architecture. This architecture with a CNN as an encoder and RNN on the top is a vanilla DRL architecture that has shown promise in multiple problem domains [Hausknecht and Stone, 2015].

At every time-step the architecture is fed three inputs: the current image I_t , the previous action a_{t-1} , and the previous reward r_{t-1} and is tasked with estimating the value function and policy at every point. Similar to their setup, we utilize auxiliary outputs of the loop closure signal L and predicted depth D_1 and D_2 to quicken training.

We use the Asynchronous advantage actor-critic (A3C) algorithm [Mnih *et al.*, 2016] to perform reinforcement learning. A3C falls in the category of policy gradient algorithms that works by jointly optimizing the policy function and the value function via the estimation of their gradients.

5 Evaluation Metrics

In addition to reporting reward, we evaluate the algorithms in terms of the *Latency-1:>1* and the *Distance-inefficiency* metrics.

Following Mirowski *et al.* [2017], we report *Latency-1:>1*, a ratio of the time taken to hit the goal for the first time (exploration time) versus the average amount of time taken to hit goal subsequently (exploitation time). To define this metric more concretely, let the position of agent at any time t be x_t . Let $\tau_{1:N} = \{t \in [0, T] \mid \|x_t - x_g\| < \epsilon\}$, be the ordered set of times when the agent hits the goal during a episode, where N is the number of times agent hits the goal and ϵ is a distance threshold on hitting the goal. Let τ_i denote the time step when the agent hits the goal i^{th} time.

$$\text{Latency-1:>1} = \frac{(N-1)\tau_1}{\tau_N - \tau_1} \quad \text{if } N \geq 2$$

This metric is a measure of how efficiently the agent exploits map information to find a shorter path once the goal location is known. If this ratio is greater than 1, the agent is doing better than random exploration and the higher the value, the better its map-exploitation ability. Note that the metric is meaningful only when the goal location is unknown at evaluation time.

Distance-inefficiency is defined to be the ratio of the total distance traveled by the agent versus the sum of approximate shortest distances to the goal from each spawn point. The metric also disregards goals found during exploration times as the agent must first find the goal before it can traverse the shortest path to it. Note that the shortest distance between the spawn and goal locations is computed as a manhattan-distance in the top-down block world perspective and hence is an approximation. Mathematically,

$$\text{Dist-ineff.} = \frac{\sum_{i=1}^{N-1} \sum_{t=\tau_i+1}^{\tau_{i+1}-1} \|x_{t+1} - x_t\|}{\sum_{i=1}^{N-1} p(x_{\tau_i+1}, x_g)} , \quad \text{if } N \geq 1$$

where $p(x_{\tau_i+1}, x_g)$ denotes the approximate shortest path distance between spawn location x_{τ_i+1} and goal location x_g .

While the Latency-1:>1 measures the factor by which subsequent paths to the goal post-goal finding is shorter than the initial exploration path, the Distance-inefficiency measures the length of this path with respect to the shortest possible path.

We report all the metrics averaged over 100 episodes of 10 randomly chosen maps in Fig 3.

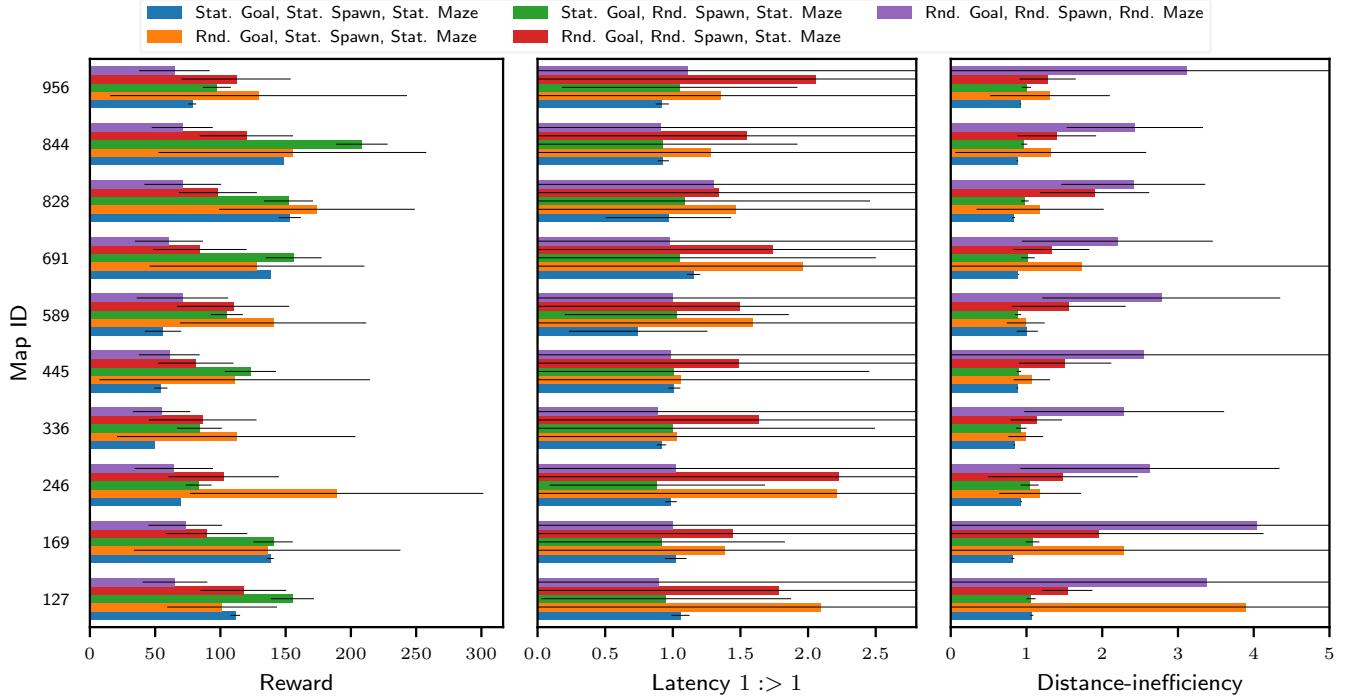


Figure 3: We evaluate the algorithm on ten randomly chosen maps with problems of increasing difficulty as described in Sec. 5.1. The vertical axis shows IDs of the ten maps from the randomly generated 1100 maps on which experimental results are repeated. We note that when the goal is static, the rewards are consistently higher as compared to random goals. With static goals, the metric Distance-inefficiency is close to 1, indicating that the algorithm is able to find the shortest path. However, with random goals, the agent struggles to find the shortest path. From the Latency-1:>1 results we note that the algorithm does well when trained and tested on the same map but fails to generalize to new maps when evaluated on the ability to exploit the information about the goal location. Note that the Latency-1:>1 metric for cases of static goals is expected to be close to one because the location of goal is learned at training time. The figure is best viewed in color.

5.1 Experiments

We evaluate the NavA3C+D₁D₂L algorithm on maps with 5 stages of difficulty, by controlling the randomness of three basic parameters: the spawn location, the goal location, and the map structure.

Spawn location We consider cases where the spawn location is *static* in all the training and testing episodes and when the spawn location is *randomized* for every spawn. Note that the agent re-spawns every time it hits the goal.

Goal location The goal location is *static* when it is fixed for all the training and testing episodes. In the random case it is *randomized* for every new episode.

Map structure In the *static map* case, we train and test on the same map. We perform static map experiments (training and testing) on ten random maps. In the *random map* case, we sample a map from 1000 maps for every episode and test on the ten maps chosen for the static map experiments. In Section 6.2, we evaluate the algorithm on a disjoint set of 100 test maps.

We investigate variations of randomness of the above parameters and propose these experiments as a 5-stage benchmark for all end-to-end navigation algorithms.

1. Static goal, static spawn, and static map To perform optimally on this experiment, the agent needs to find and

learn the shortest path at training time and repeat it during testing.

2. Static goal, random spawn and static map This is a textbook version of the reinforcement learning problem, especially in grid-world Sutton and Barto [1998], with the only difference being that the environment is partially observable instead of fully observable. This problem is more difficult than Problem 1 because the agent must find an optimal policy to the goal from each possible starting point in the maze.

3. Random goal, static spawn, and static map The agent can perform well on this experiment by remembering the goal location after it has been discovered and exploiting the information to revisit the goal faster.

4. Random goal, random spawn, and static map To perform optimally, the agent must localize itself within the map in addition to being able to exploit map-information. This is the problem that is addressed by Mirowski *et al.* [2017] with limited success. They evaluate this case on two maps and report Latency-1:>1 to be greater than 1 in one of the two maps. We evaluate the same metric on ten randomized maps.

5. Random goal, random spawn, and random map We believe that any proposed algorithms on end-to-end naviga-

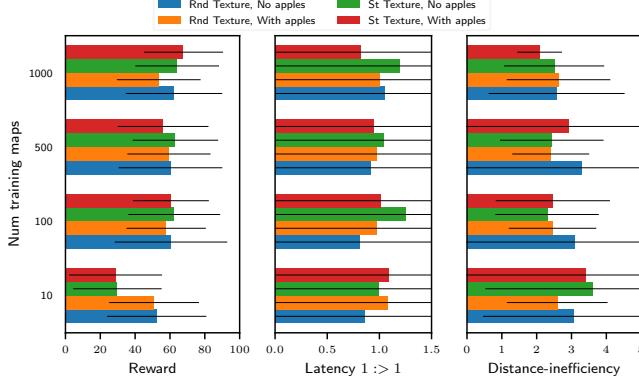


Figure 4: Plots showing the effect of number of training maps with random texture (Rnd Texture) and presence of apples (With apples), when evaluated on unseen maps. We note that the difference between metrics is negligible compared to the standard deviation of the metrics. Hence we say that the algorithm is robust to the variation of textures and to the removal of apples. Note that the mean rewards increase when the number of training maps increases from 10 to 100 maps, but that rewards remain constant thereafter despite further increases in the number of training maps.

tion problems, should be evaluated on unseen maps. To our knowledge this is the first paper to do so in the case of deep reinforcement learning based navigation methods while reporting exploitation related metrics. We train agents to simultaneously learn to explore 1000 maps and test them on 100 unseen maps. The relevant results can be found in Fig 4 and discussed in Section 6.

The comparative evaluation of the different stages of this benchmark are shown in Fig 3 and expanded upon in the Section 6.

6 Results and Analysis

We analyze the results obtained from evaluating the NavA3C+D₁D₂L on our proposed experimental suite along with qualitative and quantitative additional studies.

6.1 Static Map Experiments

In this section we discuss the results for experiments as discussed in Section 5.1 over the ten randomly chosen maps. The results are in Fig 3. The experiment titled Random goal, random spawn, random maze is trained on 1000 maps but tested on the same ten maps for comparability.

1. Static goal, static spawn, static maze For this case, the reward is consistently high, and Distance-inefficiency is close to 1 with small standard deviations implying the path chosen is the shortest available. Please note that Latency-1:>1 should be close to 1 for the static goal case because the goal location is learned at training time.

2. Static goal, random spawn, static map Again, note that Distance-inefficiency is close to 1 implying that when the goal is found, the shortest path is traversed. This is because the agent can learn the an optimal policy for the shortest path to the known goal from any location in the maze at training time.

3. Random goal, static spawn, static map In this case, the mean of the Latency-1:>1 is more than 1 showing that in general the agent is able to exploit map information. However, as confirmed by the Distance-inefficiency metric which is larger than one, that agents do not necessarily traverse the shortest path to the goal when it is found.

4. Random goal, Random spawn, static map Similar to the previous experiment, the Latency-1:>1 metric and the Distance-inefficiency metric is larger than 1 implying that while map exploitation is taking place, the paths traversed to the goal are not optimal.

5. Random goal, Random spawn, Random map For this experiment, agents trained on a 1000 maps are tested individually on the 10 chosen maps that are a subset of the 1000 maps. The Latency-1:>1 is close to 1 implying that map-exploitation is not taking place. The large Distance-inefficiency numbers confirm this statement.

6.2 Random Map Experiments

The following set of experiments are evaluated on 100 maps that are disjoint from the set of 1000 training maps.

Evaluation on unseen maps

The results for training on subsets of 1000 maps, and testing on 100 unseen maps are shown in Fig 4. We observe that there is a jump of average reward and average goal hits when the number of training maps is increased from 10 to 100 but no significant increase when the number of training maps are increased from 100 to 500 to 1000. We hypothesize that this is due to the fact that the algorithm learns an average-exploration strategy which is learned with enough variation over 100 maps and training on additional maps does not add to it.

The Latency-1:>1 and Distance-inefficiency metrics confirm that no measurable map-exploitation is taking place. We present, qualitative results in Sec. 6.2 on very simple maps to show that the agents trained on 1000 maps are only randomly exploring the maze rather than utilizing any form of shortest path planning.

Effect of apples and texture

We evaluate the effect of apples and textures during evaluation time in Fig 4. We train the algorithm on randomly chosen training maps with random textures and evaluate them on maps with and without random textures and also with and without apples. We find no significant changes across our different metrics showcasing that our training mechanism allows for creation of agent's that are robust to the presence or absence of textures and apples.

Qualitative evaluation on simple maps

To evaluate what strategies the algorithm is employing to reach the goal we evaluate the algorithm on very simple maps where there are only two paths to reach the goal. The qualitative results for the evaluation are shown in Fig 5.

Square map A Square map (Fig 5) is the simplest possible map with two paths to the goal. We evaluate the algorithm trained on 1000 random maps on this map. We observe that the agent greedily moves in the direction of initialization.

We compute the percentage of times the agent takes the shortest path over a trial of 100 episodes. We find the agent takes the shortest path only 50.4% ($\pm 12.8\%$) of the times which is no better than random.

Goal map The goal map (Fig 5) provides a decision point independent of the initial orientation. The shortest path is chosen 42.6% ($\pm 35.1\%$) of the times which is again close to random within error bounds.

These experiments show that the algorithm, even when trained on 1000 maps, does not generalize to these very simple maps highlighting how the learned navigational strategy is unable to exploit map information

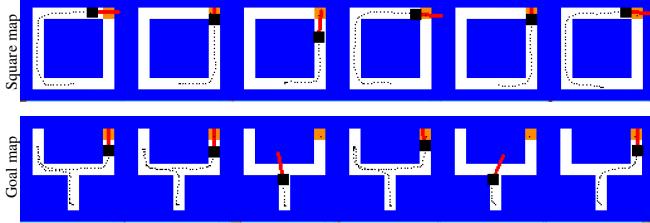


Figure 5: Snapshots of the path taken by the agent to reach the goal in a single episode when the model is trained on 1000 maps and evaluated on the Square and Goal maps. The top row shows an evaluation example on the Square map, where the agent takes the shortest path 3/6 times. The bottom row shows an evaluation example on the Goal map, where the agent takes the shortest path 1/4 times. When averaged over 100 episodes, the agent performs no better than random as the shortest path is taken 50.4% ($\pm 12.8\%$) and 42.6% ($\pm 35.1\%$) of the time for the Square map and the Goal map, respectively.

Attention heat maps

To qualitatively assess the visual cues used by agents in course of their navigation, we use the normalized sum of absolute gradient of the loss with respect to the input image as a proxy for attention in the image. The gradients are normalized for each image so that the maximum gradient is one. The attention values are then used as a soft mask on the image to create the visualization as shown in Fig 6

We observe that for most of the episode the attention narrows down to a thin band in the center of the image. We hypothesize that this narrowing down of the attention band highlights how the information required for navigation can be found within this central band. In future work, we will evaluate the performance of training agents using only this central band to see whether the resultant reward curves and metric scores are similar to that of the originals.

7 Conclusion and Future Work

In this work, we present a systematic suite of experiments to analyze DRL-based navigation algorithms. We build upon Mirowski *et al.* [2017]’s NavA3C+D₁D₂L method for analysis. We ask whether DRL algorithms are able to inherently gather and exploit environmental information over the course of the navigation of environments. Our experiments show that the algorithm is able to exploit map-information for navigation when trained and tested on same map, yet unable to do so

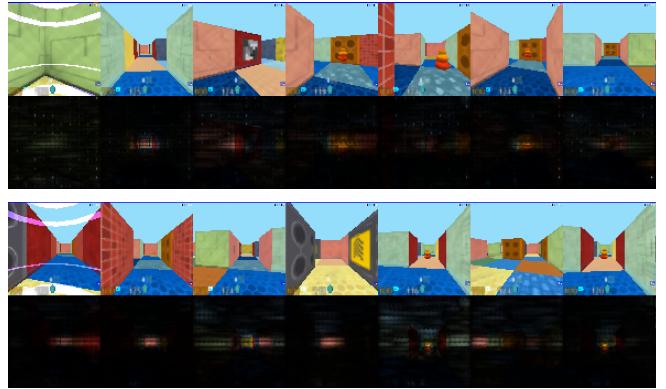


Figure 6: Visualizing attention for two sequences. The top two rows show the sequence when the model is trained on and evaluated on the same map. The bottom two rows show the sequence for a model trained on 1000 different maps and evaluated on one of those maps chosen at random. We observe that in both cases the attention is only on a few pixels in the center for the majority of the episode.

when trained and tested on different sets of maps. Even when tested and trained on the same map, the DRL algorithms fail to find the shortest path to the destination location when it is randomly chosen. These observations suggest that there is much more research to be done in DRL algorithms before they can compete with classical navigation techniques.

We believe that such rigorous investigation of DRL based navigation methods is imperative to the field moving forward, especially given the black-box nature of deep learning methods. Recent work analyzing neural networks has shown how deep learning-based can be fooled in object detection [Nguyen *et al.*, 2015] and Atari games [Kansky *et al.*, 2017]. Such levels of sensitivity motivate exactly why it is important to analyze DRL navigation methods across a wide variety of experiments: we need to comprehensively understand both their strengths and limitations. As such, we open source our experimental suite to serve as a framework for the comparison of future DRL navigation studies.

Acknowledgments

This work was supported, in part, by the US National Science Foundation under Grants 1522954-IIS and 1734938-IIS, by the Intelligence Advanced Research Projects Activity (IARPA) via Department of Interior/Interior Business Center (DOI/IBC) contract number D17PC00341, and by Siemens Corporation, Corporate Technology. Any opinions, findings, views, and conclusions or recommendations expressed in this material are those of the authors and do not necessarily reflect the views, official policies, or endorsements, either expressed or implied, of the sponsors. The U.S. Government is authorized to reproduce and distribute reprints for Government purposes, notwithstanding any copyright notation herein.

References

- John Aycock. *Procedural Content Generation*, page 135. Springer International Publishing, Cham, 2016.
- Charles Beattie, Joel Z Leibo, Denis Teplyashin, Tom Ward, Marcus Wainwright, Heinrich Küttler, Andrew Lefrancq, Simon Green,

- Víctor Valdés, Amir Sadik, et al. Deepmind lab. *arXiv preprint arXiv:1612.03801*, 2016.
- Devendra Singh Chaplot, Guillaume Lample, Kanthashree Mysore Sathyendra, and Ruslan Salakhutdinov. Transfer deep reinforcement learning in 3d environments: An empirical study. 2016.
- Alberto Elfes. Using occupancy grids for mobile robot perception and navigation. *Computer*, 22(6):46–57, 1989.
- Saurabh Gupta, James Davidson, Sergey Levine, Rahul Sukthankar, and Jitendra Malik. Cognitive mapping and planning for visual navigation. In *The IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, July 2017.
- Matthew Hausknecht and Peter Stone. Deep recurrent q-learning for partially observable mdps. *CoRR, abs/1507.06527*, 2015.
- Max Jaderberg, Volodymyr Mnih, Wojciech Marian Czarnecki, Tom Schaul, Joel Z Leibo, David Silver, and Koray Kavukcuoglu. Reinforcement learning with unsupervised auxiliary tasks. *arXiv preprint arXiv:1611.05397*, 2016.
- Ken Kansky, Tom Silver, David A Mély, Mohamed Eldawy, Miguel Lázaro-Gredilla, Xinghua Lou, Nimrod Dorfman, Szymon Sidor, Scott Phoenix, and Dileep George. Schema networks: Zero-shot transfer with a generative causal model of intuitive physics. *arXiv preprint arXiv:1706.04317*, 2017.
- Benjamin Kuipers. Modeling spatial knowledge. *Cognitive science*, 2(2):129–153, 1978.
- Tejas D Kulkarni, Ardavan Saeedi, Simanta Gautam, and Samuel J Gershman. Deep successor reinforcement learning. *arXiv preprint arXiv:1606.02396*, 2016.
- Sergey Levine, Peter Pastor, Alex Krizhevsky, and Deirdre Quillen. *Learning Hand-Eye Coordination for Robotic Grasping with Large-Scale Data Collection*, pages 173–184. Springer International Publishing, Cham, 2017.
- Piotr Mirowski, Razvan Pascanu, Fabio Viola, Hubert Soyer, Andrew J. Ballard, Andrea Banino, Misha Denil, Ross Goroshin, Laurent Sifre, Koray Kavukcuoglu, Dhruv Kumaran, and Raia Hadsell. Learning to navigate in complex environments. 2017.
- Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Alex Graves, Ioannis Antonoglou, Daan Wierstra, and Martin Riedmiller. Playing atari with deep reinforcement learning. In *NIPS Deep Learning Workshop*. NIPS, 2013.
- Volodymyr Mnih, Koray Kavukcuoglu, David Silver, Andrei A Rusu, Joel Veness, Marc G Bellemare, Alex Graves, Martin Riedmiller, Andreas K Fidjeland, Georg Ostrovski, et al. Human-level control through deep reinforcement learning. *Nature*, 518(7540):529–533, 2015.
- Volodymyr Mnih, Adria Puigdomenech Badia, Mehdi Mirza, Alex Graves, Timothy Lillicrap, Tim Harley, David Silver, and Koray Kavukcuoglu. Asynchronous methods for deep reinforcement learning. In *International Conference on Machine Learning*, pages 1928–1937, 2016.
- Anh Nguyen, Jason Yosinski, and Jeff Clune. Deep neural networks are easily fooled: High confidence predictions for unrecognizable images. In *2015 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*, pages 427–436, June 2015.
- Junhyuk Oh, V. Chockalingam, S. Singh, and H. Lee. Control of memory, active perception, and action in minecraft. In *International Conference on Machine Learning*, 2016.
- Emilio Parisotto and Ruslan Salakhutdinov. Neural map: Structured memory for deep reinforcement learning. *arXiv preprint arXiv:1702.08360*, 2017.
- David Silver, Aja Huang, Chris J Maddison, Arthur Guez, Laurent Sifre, George Van Den Driessche, Julian Schrittwieser, Ioannis Antonoglou, Veda Panneershelvam, Marc Lanctot, et al. Mastering the game of go with deep neural networks and tree search. *Nature*, 529(7587):484–489, 2016.
- Randall C Smith and Peter Cheeseman. On the representation and estimation of spatial uncertainty. *The international journal of Robotics Research*, 5(4):56–68, 1986.
- Richard S Sutton and Andrew G Barto. *Reinforcement learning: An introduction*, volume 1. MIT press Cambridge, 1998.
- Yuke Zhu, Roozbeh Mottaghi, Eric Kolve, Joseph J Lim, Abhinav Gupta, Li Fei-Fei, and Ali Farhadi. Target-driven visual navigation in indoor scenes using deep reinforcement learning. In *Robotics and Automation (ICRA), 2017 IEEE International Conference on*, pages 3357–3364. IEEE, 2017.