Towards real-world navigation with deep differentiable planners

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Abstract

We train embodied neural networks to plan and navigate unseen complex 3D environments, emphasising real-world deployment. Rather than requiring prior knowledge of the agent or environment, the planner learns to model the state transitions and rewards. To avoid the potentially hazardous trial-and-error of reinforcement learning, we focus on differentiable planners such as Value Iteration Networks (VIN), which are trained offline from safe expert demonstrations. Although they work well in small simulations, we address two major limitations that hinder their deployment. First, we observed that current differentiable planners struggle to plan long-term in environments with a high branching complexity. While they should ideally learn to assign low rewards to obstacles to avoid collisions, these penalties are not strong enough to guarantee collision-free operation. We thus impose a structural constraint on the value iteration, which explicitly learns to model impossible actions and noisy motion. Secondly, we extend the model to plan exploration with a limited perspective camera under translation and fine rotations, which is crucial for real robot deployment. Our proposals significantly improve semantic navigation and exploration on several 2D and 3D environments, succeeding in settings that are otherwise challenging for differentiable planners. As far as we know, we are the first to successfully apply them to the difficult Active Vision Dataset, consisting of real images captured from a robot.1

1. Introduction

Continuous advances in robotics have enabled robots to be deployed to a wide range of scenarios, from manufacturing in factories and cleaning in households, to the emerging applications of autonomous vehicles and delivery drones [2]. Improving their autonomy is met with many challenges, due to the difficulty of planning from uncertain sensory data. In classical robotics, the study of planning has a long tradi-

1Code available: https://github.com/shuishida/calvin
ner. Being sub-differentiable, like all other elements of a deep network, allows the planner to include learnable elements, trained end-to-end from example data. For example, it can learn to identify and avoid obstacles, and to recognise and seek classes of target objects, without explicitly labelled examples. However, there are gaps between VIN’s idealised formulation and realistic robotics scenarios, which some works address [12, 21]. The CNN-based VIN [43] considers that the full environment is visible and expressible as a 2D grid. As such, it does not account for embodied (first-person) observations in 3D spaces, unexplored and partially-visible environments, or the mismatch between egocentric observations and idealised world-space discrete states.

In this paper we address these challenges, and close the gap between current differentiable planners and realistic robot navigation applications. Our contributions are:

1. A constrained transition model for value iteration, following a rigorous probabilistic formulation, which explicitly models illegal actions and task termination (Sec. 4.1). This is our main contribution.

2. A 3D state-space for embodied planning through the robot’s translation and rotation (Sec. 4.2.1). Planning through fine-grained rotations is often overlooked (Sec. 2), requiring better priors for transition modelling (Sec. 4.1.2).

3. A trajectory reweighting scheme that addresses the unbalanced nature of navigation training distributions (Sec. 4.1.5).

4. We demonstrate for the first time that differentiable planners can learn to navigate in both complex 3D mazes, and the challenging Active Vision Dataset [1], with images from a real robot platform (Sec. 5.2.2). Thus our method can be trained with limited data collected offline, as opposed to limitless data from a simulator as in prior work.

Sec. 2 discusses related work, while Sec. 3 gives a short introduction to differentiable planning. Sec. 4 presents our technical proposals, and Sec. 5 evaluates them.

2. Related work

Planning and reinforcement learning. Planning in fully-known deterministic state spaces was partially solved by graph-search algorithms [10, 15, 22–24, 41]. A Markov Decision Process (MDP) [3, 42] considers probabilistic transitions and rewards, enabling planning on stochastic models and noisy environments. With known MDPs, Value Iteration achieves the optimal solution [3, 42]. Reinforcement Learning (RL) focuses on unknown MDPs [29, 29, 36, 45, 46]. Model-free RL systems are reactive; a policy (i.e. a generic plan) is built over a long period of trial and error, and will be specific to the training environment (there is no online planning). This makes them less ideal for robotics, where risky failures must be avoided, and new plans (policies) must be created on-the-fly in new environments. Model-based RL methods attempt to learn an MDP and often use it for planning online [9, 13, 14, 19, 20]. The environment is assumed to provide a reward signal at every step in both cases.

Deep networks for navigation. Several works have made advances into training deep networks for navigation. The Neural Map [34] is an A2C [29] agent (thus reactive) that reads and writes to a differentiable memory (i.e. a map). Similarly, Mirowski et al. [28] train reactive policies which are specific to an environment. The Value Prediction Network [33] learns an MDP and its state-space from data, and plans with a single roll-out over a short horizon. Hausknecht et al. [16] add recurrence to deep Q-learning to address partially-observable environments, but considering only single-frame occlusions. Several works treat planning as a non-differentiable module, and focus on training neural networks for other aspects of the navigation system. Savinov et al. [37] do this by composing siamese networks and value estimators trained on proxy tasks, and use an initial map built from footage of a walk through the environment. Active Neural SLAM [6] trains a localisation and mapping component (outputting free space and obstacles), a policy network to select a target for the non-differentiable planner, and another to perform low-level control. Subsequent work [5] complemented this map with semantic segmentation. This map is different from ours, which consists of embeddings learned by a differentiable planner, and so are not constrained to correspond to annotated labels. The later two works navigate successfully in large simulations of 3D-scanned environments, and were transferred to real robots.

Imitation learning. To avoid learning by trial-and-error, Imitation Learning instead uses expert trajectories. Inverse Reinforcement Learning (IRL) [18, 31, 48, 49] achieves this by learning a reward function that best explains the expert trajectories. However, this generally leads to a difficult nested optimisation and is an ill-posed problem, since many reward functions can explain the same trajectory.

Differentiable planning. Tamar et al. [43] introduced the Value Iteration Network (VIN) for Imitation Learning, which generates a plan online (with value iteration) and back-propagates errors through the plan to train estimators of the rewards (Sec. 3.1). VINs were also applied to localisation from partial observations by Karkus et al. [21], but assuming a full map of the environment. Lee et al. [25] replaced the maximum over actions in the VI formula with a LSTM. The evaluation included an extension to rotation, but assuming a fully-known four directional view for every gridded state, which is often not available in practice. A subtle difference is that they handle rotation by applying a linear policy layer to the hidden channels of a 2D state-space grid, which is less interpretable than our 3D translation-rotation grid.

Most previous work on deploying VIN to robots [32, 38] assume an occupancy map and goal map rather than learning the map embedding and goal themselves from data. To
the best of our knowledge, Gupta et al.’s Cognitive Mapper and Planner (CMP) [12] is the only work which evaluated a differentiable planner on real-world data using map embeddings learned end-to-end. CMP uses a hierarchical VIN [43] to plan on larger environments, and updates an egocentric map. It handles rotation as a warping operation external to the VIN (i.e. it plans in a 2D translation state-space, not 3D translation-rotation space). Warping an egocentric map per update achieves scalability at the cost of progressive blurring of the embeddings. CMP was evaluated for rotations of $90^\circ$ and deterministic motion, rather than noisy translation and rotation. Our 3D translation-rotation space and learned transition model allows smooth trajectories with finer rotations. CMP also requires gathering new trajectories online during training (with DAgger [35]), while ours is trained solely with a fixed set of training trajectories, foregoing the need for a simulator and the associated domain gap.

3. Background

A Markov Decision Process (MDP) [3, 42] formalises sequential decision-making. It consists of states $s \in S$ (e.g. locations), actions available at each state $a \in A(s)$, a reward function $R(s, a, s')$ to be maximised (e.g. reaching the target), and a transition probability $P(s'|s, a)$ (the probability of the next state $s'$ given the current state $s$ and action $a$). The objective of an agent is to learn a policy $\pi(a|s)$, specifying the probability of choosing action $a$ for any state $s$, chosen to maximise the expected return $G_t$ at every time step $t$. A return is a sum of discounted rewards, $G_t = \sum_{k=0}^{\infty} \gamma^k R_{t+k+1}$, where a discount factor $\gamma \in (0, 1)$ prevents divergences of the infinite sum. The value function $V_\pi(s) = \mathbb{E}_\pi[G_t|s_t = s]$ evaluates future returns from a state, while the action-value function $Q_\pi(s, a)$ = $\mathbb{E}_\pi[G_t|s_t = s, a_t = a]$ considers both a state and the action taken. An optimal policy $\pi_*$ should then maximise the expected return for all states, i.e. $\forall s \in S, v_\pi(s) = \max_\pi v_\pi(s)$. Value Iteration (VI) [3, 42] is an algorithm to obtain an optimal policy, by alternating a refinement of both value ($V$) and action-value ($Q$) function estimates in each iteration $k$. When $s$ and $a$ are discrete, $Q(k)$ and $V(k)$ can be implemented as simple tables (tensors). In particular, we will consider as states the cells of a 2D grid, corresponding to discretised locations in an environment, i.e. $s = (i, j) \in S = \{1, \ldots, N\}^2$. Furthermore, transitions are local (only to coordinates offset by $\delta \in K = \{-1, 0, 1\}^2$):

$$Q^{(k)}_{a,s} = \sum_{\delta \in K} P_{a,\delta,s} \left( R_{a,\delta,s} + \gamma V^{(k-1)}_{s+\delta} \right)$$

$\forall a \in A(s)$, with $V^{(k)}_s = \max_{a \in A(s)} Q^{(k)}_{a,s}$. (1)

Note that to avoid repetitive notation $s$ and $\delta$ are 2D indices, so $V$ is a 2D matrix and both $R$ and $P$ are 5D tensors. The policy $\pi^{(k)}_s$ = $\arg\max_{a \in A(s)} Q^{(k)}_{a,s}$ simply chooses the action with the highest action-state value. While the sum in Eq. 1 resembles a convolution, the filters ($P$) are space-variant (depend on $s = (i, j)$), so it is not directly expressible as such. Eq. 1 represents the “ideal” VI for local motion on a 2D grid, without further assumptions.

3.1. Value Iteration Network

While VI guarantees the optimal policy, it requires that the functions for transition probability $P$ and reward $R$ are known (e.g. defined by hand). Tamar et al. [43] pointed out that all VI operations are (sub-)differentiable, and as such a model of $P$ and $R$ can be trained from data by back-propagation. For the case of planning on a 2D grid (navigation), they related Eq. 1 to a CNN, as:

$$Q^{(k)}_{a,s} = \sum_{\delta \in K} \left( P_{a,\delta,R_s+\delta}^R + P_{a,\delta,V_s+\delta}^V \right)$$

$\forall a \in A$, with $V^{(k)}_s = \max_{a \in A} Q^{(k)}_{a,s}$. (2)

where $P^R, P^V \in \mathbb{R}^{A \times |K|}$ are two learned convolutional filters that represent the transitions ($P$ in Eq. 1), and $\hat{R}$ is a predicted 2D reward map. Note that $A$ is independent of $s$, i.e. all actions are allowed in all states. This turns out to be detrimental (see next paragraph). The reward map $\hat{R}$ is predicted by a CNN, from an input of the same size that represents the available observations. In Tamar et al.’s experiments [43], the observations were a fully-visible overhead image of the environment, from which negative rewards such as obstacles and positive rewards such as navigation targets can be located. Each action channel in $A$ corresponds to a move in the 2D grid, typically 8-directional or 4-directional. Eq. 2 is attractive, because it can be implemented as a CNN consisting of alternating convolutional layers ($Q$) and max-pooling along the actions (channels) dimension ($V$).

Motivating experiment. Since the VIN allows all actions at all states ($A$ does not depend on $s$), collisions must be modelled as states with low rewards. In practice, the VIN does not learn to forbid such actions completely, resulting in
With these assumptions, the reward function $R$ was introduced in the VIN to allow efficient learning with which is another failure mode. We aim to fix these issues, upon triggering an incorrect action. We denote the reward for $\hat{s}$ as a special case of reaching in addition to positional states, we assume a success state $s$ is available from state (“done”), and a failure state $F$ (“fail”) that is reached upon triggering an incorrect action. We denote the reward for reaching $F$ as $R_F$, and the translation-invariant rewards as $\hat{R}(a,s')$. For simplicity, we consider the reward for success a special case of $\hat{R}(a,s'-s)$ where $a = D$ and $s' = W$. With these assumptions, the reward function $R(s,a,s')$ is:

$$R(s,a,s') = \begin{cases} \hat{R}_F, & s' = F \\ \hat{R}(a,s'-s), & s' \neq F. \end{cases}$$  

Together with the agent motion model $\hat{P}(s'|s,a)$, action validity predictor $\hat{A}(s,a)$ and the definition of a failure state $F$, the transition model $P(s'|s,a)$ can be derived as Eq. 4:

$$P(s'|s,a) = \begin{cases} 1 - \hat{A}(s,a), & s' = F \\ \hat{A}(s,a)\hat{P}(s' - s|a), & s' \neq F. \end{cases}$$  

From the above, we calculate the reward $R(s,a)$ by marginalising over the neighbour states $s'$:

$$R(s,a) = \sum_{s'} P(s'|s,a)R(s,a,s')$$  

$$= \hat{R}_F(1 - \hat{A}(s,a)) + \hat{A}(s,a)\sum_{s'} \hat{P}(s' - s|a)\hat{R}(a,s'-s)$$

Finally, Eq. 5 can be plugged into Eq. 1 to obtain our proposed value iteration’s $Q(s,a)$:

$$Q(s,a) = R(s,a) + \gamma\sum_{a'} P(s'|s,a)V(s')$$  

$$= R(s,a) + \gamma\hat{A}(s,a)\sum_{a \neq D} \hat{P}(s' - s|a)V(s')$$

where $\mathbb{1}$ is an indicator function. Eq. 5 and 6 essentially express a constrained VI, which models the case of an MDP on a grid with unknown illegal states and termination at a goal state. The inputs to this model are three learnable functions — the motion model $\hat{P}(s'-s|a)$, the action validity $\hat{A}(s,a)$ (i.e. obstacle predictions), and the rewards $\hat{R}(a,s'-s)$ and $\hat{R}_F$. These are implemented as CNNs with the observations as inputs ($\hat{R}_F$ is a single learned scalar). All the constraints follow from a well-defined world-model, with very interpretable predicted quantities, unlike previous proposals [25, 43]. We named this method Collision Avoidance Long-term Value Iteration Network (CALVIN).

### 4.1. Augmented navigation state-action space

In this section we will derive a probabilistic transition model from first principles, with only two assumptions and no extra hyper-parameters. The first assumption is locality and translation invariance of the agent motion, which was introduced in the VIN to allow efficient learning with shared parameters. Unlike the VIN, we will decompose the transition model $P(s'|s,a)$ into two components: the agent motion model $\hat{P}(s'-s|a)$, which is translation invariant and shared across states (depending only on the spatial difference between states $s'-s$); and an observation-dependent predictor $\hat{A}(s,a) \in [0,1]$ which evaluates whether action $a$ is available from state $s$, to disqualify illegal actions.

In robotics, it is essential that the agent understands that the current task has been completed to move on to the next one. Since in small environments there is a high chance that a randomly-acting agent will stumble upon the target, Anderson et al. [2] suggested that an explicit termination action must be taken at the target to finish successfully. Therefore, in addition to positional states, we assume a success state $W$ (“win”) that is reached only by triggering a termination action $D$ (“done”), and a failure state $F$ (“fail”) that is reached upon triggering an incorrect action. We denote the reward for reaching $F$ as $R_F$, and the translation-invariant rewards as $\hat{R}(a,s'-s)$. For simplicity, we consider the reward for success a special case of $\hat{R}(a,s'-s)$ where $a = D$ and $s' = W$. With these assumptions, the reward function $R(s,a,s')$ is:

Where $Q(s)$ is a vector with one element per action $(Q(s,a))$, and $w_1$ is an optional weight that can be used to bias the loss if $w_1 \neq 1$ (Sec. 4.1.5). Example trajectories are shortest paths computed from random starting points to the target (also chosen randomly). Note that the learned functions can be conditioned on input observations. These are 2D grids of features, with the same size as the considered state-space (i.e. a map of observations), which is convenient since it enables $\hat{P}$, $\hat{A}$ and $\hat{R}$ to be implemented as CNNs.
4.1.2 Transition modelling

Similarly to the VIN (Eq. 2), the motion model \( \hat{P}(s' - s|a) \) is implemented as a convolutional filter \( \hat{P} \in \mathbb{R}^{|A| \times |K|} \), so it only depends on the relative spatial displacement \( s' - s \) between the two states \( s \) and \( s' \). We can use the transitions already observed in the example trajectory to constrain the model, by adding a cross-entropy loss term \( L(A(s')_t, s_{t+1} - s_t) \) for each step in the example trajectory. After training, the filter \( \hat{P}(s' - s|a) \) will consist of a distribution over possible state transitions for each action (visualised in Fig. 5).

4.1.3 Action availability

Although the available actions \( \hat{A} \) could, in theory, be learned completely end-to-end, in practice we found that additional regularisation is necessary. If we had a reliable log-probability of each action being taken, \( \hat{A}_{\text{logit}}(s, a) \), then by thresholding it at some point \( \hat{A}_{\text{thresh}}(s) \) we would distinguish between available and unavailable actions. Using a sigmoid function \( \sigma \) as a soft threshold, we can write this as:

\[
\hat{A}(s, a) = \sigma(\hat{A}_{\text{logit}}(s, a) - \hat{A}_{\text{thresh}}(s)). \tag{8}
\]

Both \( \hat{A}_{\text{logit}}(s, a) \) and \( \hat{A}_{\text{thresh}}(s) \) are predicted by the network, given the observations at each time step. In order to ground the probabilities of each action being taken, we encourage the actions \( \hat{A}_{\text{logit}}(s_t) \) to match the example trajectory action \( a^*_t \) for all steps \( t \), with an additional cross-entropy loss \( L(\hat{A}_{\text{logit}}(s_t, a^*_t)) \). Note that there is no additional ground truth supervision – we use strictly the same data as a VIN.

4.1.4 Fully vs. partially observable environments

Some previous works [25, 43] assume that the entire environment is static and fully observable, which is often unrealistic. Partially observable environments, involving unknown scenes, require exploring to gather information and are thus more challenging. We account for this with a simple but significant modification. Note that \( Q(s_t) \) in Eq. 7 depends on the learned functions (CNNs) \( \hat{P}, \hat{A} \) and \( \hat{R} \) through Eq. 6, and these in turn are computed from the observations. We extend the VIN framework to the case of partial observations by ensuring that \( Q(s_t|O_{\leq t}) \) depends only on the observations up to time \( t \), \( O_{\leq t} \). This means that the VIN recomputes a plan at each step \( t \) (since the observations are different), instead of once for a whole trajectory. Unobserved locations have their features set to zero, so in practice knowledge of the environment is slowly built up during an expert demonstration, which enables exploration behaviour to be learned.

4.1.5 Trajectory reweighting

Exploration provides observations \( O_{\leq t} \) of the same locations at different times (Sec. 4.1.4). We can thus augment Eq. 7 with these partial observations as extra samples. The sum in Eq. 7 becomes \( \sum_{t' \in T} \sum_{t \in T_t} w_t L(Q(s_t|O_{\leq t'}), a^*_t) \). For long trajectories, the training data then becomes severely unbalanced between exploration (target not visible) and exploitation (target visible), with a large proportion of the former (90% of the data in Sec. 5.1.2). We addressed this by reweighting the samples. We set \( w_t = \beta^{T_t - t} \) in Eq. 7, i.e. a geometric decay scaling with the topological distance to the target \( d_t \). Since expert trajectories are shortest paths, this simplifies to \( w_t = \beta^{t|T| - t} \).

4.2 Embodied navigation in 3D environments

Embodied agents such as robots have a pose in 3D space, which for non-holonomic robots limits their available actions (e.g. moving forward or rotating), and their observations.

4.2.1 Embodied pose states (position and orientation)

To address the first limitation, we augment the 2D state-space with an extra dimension, which corresponds to \( \Theta \) discretised orientations: \( S = \{1, \ldots, N\}^2 \times \{1, \ldots, \Theta\} \). This can be achieved by directly adding one extra dimension to each spatial tensor in Eq. 5 and 6. A table of tensor sizes is in Appendix A. Note that the much larger state-space makes long-term planning more difficult to learn. We observed that when naively augmenting the state-space in this way, the models fail to learn correct motion kernels \( \hat{P}(s' - s|a) \). This further reinforces the need for an auxiliary motion loss (Sec. 4.1.2), which overcomes this obstacle, and may explain why prior works did not plan through fine-grained rotations.

4.2.2 3D embeddings for geometric reasoning

To aggregate image information (CNN embeddings) on to the 2D grid (map) where VIN performs planning, we follow the same strategy as MapNet [17]. Each embedding is associated with a 3D point in world-space via projective geometry, assuming that the camera poses and depths are known (as assumed in prior work [4, 12, 25, 26, 43], which can be estimated from monocular vision [30]). The embeddings of 3D points from all past frames that fall into each cell of the world-space 2D grid are aggregated with mean-pooling. Due to the use of PointNet [7] aggregation on cells of a lattice, we named this Lattice PointNet (LPN). A self-contained description is in Appendix A. The LPN has some appealing properties in our context of navigation: 1) it allows reasoning about far away, observed but yet unvisited locations; 2) it fuses multiple observations of the same location, whether from different points-of-view or different times.

**Memory-efficient mapping.** Temporal aggregation during rollout can be computed recursively as \( e_{t,i,j,k} = e_{t-1,i,j,k} + e'_{t,i,j,k} \) and \( n_{t,i,j,k} = n_{t-1,i,j,k} + n'_{t,i,j,k} \). Here, \( e_{t,i,j,k} \) is the summed embedding for the
with a minimum topological distance from the (random) start.

We assume the agent’s pose, \( A \), is required. The algorithm [47] is the same methods in unknown environments. Other than using mazes instead of convex obstacles, this setting is close to Tamar et al.’s [43]. The VIN, GPPN and CALVIN all use 2-layer CNNs to predict their inputs (details in Appendix A). All networks are trained with 4K example trajectories in an equal number of different mazes, using the Adam optimiser with the optimal learning rate chosen from \{0.01, 0.005, 0.001\}, until convergence (up to 30 epochs). Navigation success rate, averaged over 3 random seeds (and the standard deviation). The VIN has a low success rate, showing that it does not scale to large mazes. GPPN achieves a high success rate, and CALVIN performs near-perfectly. This may be explained by the GPPN’s higher capacity, as it contains a LSTM with more parameters. Nevertheless, CALVIN has a more constrained architecture, so its higher performance hints at a better inductive bias for navigation. It is interesting to note that the proposed reweighted loss has a beneficial effect on all methods, not just CALVIN. With the correct data distribution, any method with sufficient capacity can fit the objective. This shows that addressing the unbalanced nature of the data is an important, complementary factor.

### Table 1. Navigation success rate (fraction of trajectories that reach the target) on unseen 2D mazes.

| Setting                        | Standard loss | Reweighted loss (ours) | Baselines and training. For the first experiment, we compare our method (CALVIN) with other differentiable planners: the VIN [43] and the more recent GPPN [25], on fully-observed environments. Other than using mazes instead of convex obstacles, this setting is close to Tamar et al.’s [43]. The VIN, GPPN and CALVIN all use 2-layer CNNs to predict their inputs (details in Appendix A). All networks are trained with 4K example trajectories in an equal number of different mazes, using the Adam optimiser with the optimal learning rate chosen from \{0.01, 0.005, 0.001\}, until convergence (up to 30 epochs). Navigation success rate, averaged over 3 random seeds (and the standard deviation). The VIN has a low success rate, showing that it does not scale to large mazes. GPPN achieves a high success rate, and CALVIN performs near-perfectly. This may be explained by the GPPN’s higher capacity, as it contains a LSTM with more parameters. Nevertheless, CALVIN has a more constrained architecture, so its higher performance hints at a better inductive bias for navigation. It is interesting to note that the proposed reweighted loss has a beneficial effect on all methods, not just CALVIN. With the correct data distribution, any method with sufficient capacity can fit the objective. This shows that addressing the unbalanced nature of the data is an important, complementary factor.

### Figure 3. Our method on 2D mazes (Sec. 5.1.3).

(Left) Input visualisation: unexplored cells are dark, the target is yellow (just found by the agent), and a black arrow shows the agent’s position and orientation. (Middle) Close-up of predicted rewards (higher values are brighter) inside the white rectangle of the left panel. The 3D state-space (position/orientation) is shown, with rewards for the 8 orientations in a radial pattern within each cell (position). Explored cells have low rewards, with the highest reward at the target. (Right) Close-up of predicted values. They are higher facing the direction of the target. Obstacles (black border) have low values.

### 5.1.1 Fully-known environment with positional states

#### Baselines and training.

For the first experiment, we compare our method (CALVIN) with other differentiable planners: the VIN [43] and the more recent GPPN [25], on fully-observed environments. Other than using mazes instead of convex obstacles, this setting is close to Tamar et al.’s [43]. The VIN, GPPN and CALVIN all use 2-layer CNNs to predict their inputs (details in Appendix A). All networks are trained with 4K example trajectories in an equal number of different mazes, using the Adam optimiser with the optimal learning rate chosen from \{0.01, 0.005, 0.001\}, until convergence (up to 30 epochs). Navigation success rate, averaged over 3 random seeds (and the standard deviation). The VIN has a low success rate, showing that it does not scale to large mazes. GPPN achieves a high success rate, and CALVIN performs near-perfectly. This may be explained by the GPPN’s higher capacity, as it contains a LSTM with more parameters. Nevertheless, CALVIN has a more constrained architecture, so its higher performance hints at a better inductive bias for navigation. It is interesting to note that the proposed reweighted loss has a beneficial effect on all methods, not just CALVIN. With the correct data distribution, any method with sufficient capacity can fit the objective. This shows that addressing the unbalanced nature of the data is an important, complementary factor.

### 5.1.2 Partially observable environment

#### Setting.

Next, we compare the same methods in unknown environments, where the observation maps only contain ob-
Table 2. Navigation success rate on unseen 3D mazes (MiniWorld). Note that the baselines do not generalise to larger mazes.

| Size     | A2C | PPO | VIN    | GPPN  | CALVIN (ours) |
|----------|-----|-----|--------|-------|---------------|
| $3 \times 3$ | $98.7_{\pm 1.9}$ | $91.3_{\pm 4.7}$ | $97.7_{\pm 1.7}$ |
| $8 \times 8$  | $23.6_{\pm 4.9}$  | $41.2_{\pm 3.6}$  | $69.2_{\pm 5.3}$  |

We now integrate the Lattice PointNet (LPN, Sec. 4.2.2) to handle first-person views of 3D environments, which performs well. Note that to succeed, an agent must acquire several complex behaviours: directing exploration to large unseen areas; backtracking from dead ends; and seeking the target when seen. Our method displays all of these behaviours (see Appendix A for visualisations). While the model initially assigns high values to all unexplored states, as soon as the target is in view, the model assigns a high value to the target state and its neighbours. Since only a combination of CALVIN and a reweighted loss works at all, we infer that a correct inductive bias and a balanced data distribution are both necessary for success.

5.1.3 Embodied navigation with orientation

**Setting.** Now we consider embodied navigation, where transitions depend on the agent’s orientation (sec. 4.2.1). We augment the state-space of all methods (Sec. 4.2.1) with 8 orientations at $45^\circ$ intervals, and allow 4 move actions $A$: forward, backward, and rotating in either direction.

**Results.** In Tab. 1 (3rd row) we observe that VIN and GPPN perform slightly better, but still have a low chance of success. CALVIN outperforms them by a large margin. We also visualise a typical run in Fig. 3 (refer to the caption for more detailed analysis). One advantage of CALVIN displayed in Figs. 2 and 3 is that values and rewards are fully interpretable and play the expected roles in value iteration (Eq. 1). Less constrained architectures $[25, 43]$ insert operators that deviate from the value iteration formulation, and thus lose their interpretability as rewards and values (cf. Appendix A).

5.2. 3D environments

Having validated embodied navigation and exploration, we now integrate the Lattice PointNet (LPN, Sec. 4.2.2) to handle first-person views of 3D environments.

5.2.1 Synthetically-rendered environments

**Dataset.** We used the MiniWorld simulator $[8]$, which allowed us to easily generate 3D maze environments with arbitrary layouts. Only a monocular camera is considered (not 360° views $[25]$). The training trajectories now consist of first-person videos of the shortest path to the target, visualised in Fig. 4. We randomly generate 1K trajectories in mazes on either small ($3 \times 3$) or large ($8 \times 8$) grids by adding or removing walls at the boundaries of this grid’s cells. Note that the maze’s layout and the agent’s location do not necessarily align with the 2D grids used by the planners (as in $[25]$). Thus, planning happens on a fine discretisation of the state-space ($30 \times 30$ for small mazes and $80 \times 80$ for large ones, with 8 orientations). This allows smooth motions and no privileged information about the environment. Both translation and rotation are perturbed by Gaussian noise, forcing all agents to model uncertain dynamics.

**Baselines and training.** We compare several baselines: two popular RL methods, A2C $[29]$ and PPO $[39]$, as well as the VIN, GPPN and the proposed CALVIN. Since A2C and PPO are difficult to train if triggering the “done” action is strictly required, we relaxed the assumption, allowing the agent to terminate once it is in close proximity to the target. All methods use as a first stage a simple 2-layer CNN (details in Appendix A). Since this CNN was not enough to get the VIN, GPPN and CALVIN to work well (see Appendix A), they all use our proposed LPN backbone. We could not include GPPN’s strategy of taking as input views at all possible states $[25]$, due to the high memory requirements and the environment not being fully visible (only local views are available). Other training details are identical to Sec. 5.1.

**Results.** In Tab. 2 we observe that, although the RL methods are successful in small mazes, their reactive policies cannot scale to large mazes. CALVIN succeeds reliably even for longer trajectories, outperforming the others. It is interesting to note that the proposed LPN backbone is important for all differentiable planners, and it allows them to achieve very high success rates for small environments (though our CALVIN method performs slightly better). We show an example run of our method in Fig. 4, where it found the target after an efficient exploration period, despite not knowing its location and never encountering this maze before.

Figure 5 visualises the learnt state transitions $\hat{P}(s'|s|a)$ for the move forward action in CALVIN. We observe that the learning mechanism outlined in Sec. 4.1.2 works even for transitions with added noise, which is the case for MiniWorld experiments. The network learns to propagate values probabilistically from the possible next states.

5.2.2 Indoor images from a real-world robot

Finally, we tested our method on real images obtained with a robotic platform.
Dataset. We used the Active Vision Dataset [1] (AVD), which allows interactive navigation with real image streams, without synthetic rendering (as opposed to [27]). This is achieved using monocular RGBD images from 19 indoor environments, densely collected by a robot on a 30cm grid and at 30° rotations. The set of over 30K images can be composed to simulate any trajectory, up to the some spatial granularity. There are also bounding box annotations of object instances, which we use to evaluate semantic navigation. We use the last four environments as a validation set, and the rest for training (by sampling 1K shortest paths to the target). A visualisation is shown in Fig. 1.

Tasks and training. We considered a semantic navigation task of seeking an object of a learnt class. We chose the most common class (“soda bottle”) as a target object. Training follows Sec. 5.2.1.

Results. We report the performances of VIN, GPPN and CALVIN in Tab. 3 after 8 epochs of training. As in Sec. 5.2.1, they also fail without the LPN, so all results are with the LPN backbone. A similar conclusion to that for synthetic environments can be drawn: proper spatio-temporal aggregation of local observations is essential for differentiable planners to scale realistically. CALVIN achieves a significantly higher success rate on the training set than the other methods. On the other hand, while it has higher mean validation success, the high variance of this estimate does not allow the result to be as conclusive as for training. We can attribute this to the small size of AVD in general, and of the validation set in particular, which contains only 3 different indoor scenes. Nevertheless, this shows that CALVIN learns effective generic strategies to seek a specific object, and that VIN and GPPN equipped with a similar backbone can achieve partial success in several training environments.

6. Discussion

We analysed several shortcomings of current differentiable planners, with the goal of deploying to real robot platforms. We found that they can be addressed by highly complementary solutions: a constrained transition model (CALVIN) correctly incorporates illegal actions (as opposed to simply discouraging them via rewards) and task termination; a 3D state-space accounts for robot orientation; a LPN backbone efficiently fuses spatio-temporal information; and trajectory reweighting addresses unbalanced training data. We provide empirical evidence in several settings, including on images of unseen environments from a real robot.

Although deep networks hold promise for making navigation more robust under uncertainty, their uninterpretable failure modes mean that they are not yet mature enough for safety-critical applications, and more research to close this gap is still needed. Vehicle applications are especially important, due to the high masses and velocities involved. We propose a more interpretable MDP structure for VINs, and train our model solely with safe offline demonstrations. However, their reliability is far from guaranteed, and complementary safety systems in hardware must be considered in any deployment. In addition to further improving robustness to failures, future work may investigate more complex tasks, such as natural language commands, and study the effect of sensor drift on navigation performance.

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References

[1] Phil Ammirato, Patrick Poirson, Eunbyung Park, Jana Kosecka, and Alexander C. Berg. A dataset for developing and benchmarking active vision. In 2017 IEEE International Conference on Robotics and Automation (ICRA), pages 1378–1385, 2017. 2, 8

[2] Peter Anderson, Angel Chang, Devendra Singh Chaplot, Alexey Dosovitskiy, Saurabh Gupta, Vladlen Koltun, Jana Kosecka, Jitendra Malik, Roozbeh Mottaghi, Manolis Savva, et al. On evaluation of embodied navigation agents. arXiv preprint arXiv:1807.06757, 2018. 1, 4

[3] Richard Bellman. A Markovian Decision Process. Indiana University Mathematics Journal, 6(4):679–684, 1957. 2, 3

[4] Vincent Cartillier, Zhile Ren, Neha Jain, Stefan Lee, Irfan Essa, and Dhruv Batra. Semantic mapnet: Building allocentric semantic maps and representations from egocentric views, 2021. 5

[5] Devendra Singh Chaplot, Dhiraj Gandhi, Abhinav Gupta, and Ruslan Salakhutdinov. Object goal navigation using goal-oriented semantic exploration. In In Neural Information Processing Systems, 2020. 2

[6] Devendra Singh Chaplot, Dhiraj Gandhi, Saurabh Gupta, Abhinav Gupta, and Ruslan Salakhutdinov. Learning to Explore using Active Neural SLAM. In International Conference on Learning Representations, page 18, 2020. 2

[7] R. Qi Charles, Hao Su, Mo Kaichun, and Leonidas J. Guibas. PointNet: Deep Learning on Point Sets for 3D Classification and Segmentation. In 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR), pages 77–85, Honolulu, HI, July 2017. IEEE. 5

[8] Maxime Chevalier-Boisvert. Gym-MiniWorld environment for OpenAI Gym. https://github.com/maximecb/gym-mineworld, 2018. 7, 8

[9] Ignasi Clavera, Jonas Rothfuss, John Schulman, Yasuhiro Fujita, Tamim Asfour, and Pieter Abbeel. Model-based reinforcement learning via meta-policy optimization. In Conference on Robot Learning, pages 617–629. PMLR, 2018. 2

[10] E. W. Dijkstra. A note on two problems in connexion with graphs. Numerische Mathematik, 1959. 2

[11] Ian Goodfellow, Yoshua Bengio, Aaron Courville, and Yoshua Bengio. Deep learning, volume 1. MIT press Cambridge, 2016. 1

[12] Saurabh Gupta, Varun Tolani, James Davidson, Sergey Levine, Rahul Sukthankar, and Jitendra Malik. Cognitive Mapping and Planning for Visual Navigation. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition, 2017. arXiv: 1702.03920, 2, 3, 5

[13] Danijar Hafner, Timothy Lillicrap, Jimmy Ba, and Mohammad Norouzi. Dream to control: Learning behaviors by latent imagination. arXiv preprint arXiv:1912.01603, 2019. 2

[14] Danijar Hafner, Timothy Lillicrap, Ian Fischer, Ruben Villegas, David Ha, Honglak Lee, and James Davidson. Learning latent dynamics for planning from pixels. In International Conference on Machine Learning, pages 2555–2565. PMLR, 2019. 2

[15] P. E. Hart, N. J. Nilsson, and B. Raphael. A formal basis for the heuristic determination of minimum cost paths. IEEE Transactions on Systems Science and Cybernetics, 1968. 2

[16] Matthew Hausknecht and Peter Stone. Deep recurrent q-learning for partially observable mdps. arXiv preprint arXiv:1507.06527, 2015. 2

[17] Joao F. Henriques and Andrea Vedaldi. MapNet: An Allocentric Spatial Memory for Mapping Environments. In 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 8476–8484, June 2018. ISSN: 1063-6919. 5

[18] Jonathan Ho and Stefano Ermon. Generative Adversarial Imitation Learning. In D. D. Lee, M. Sugiyama, U. V. Luxburg, I. Guyon, and R. Garnett, editors, Advances in Neural Information Processing Systems 29, pages 4565–4573, 2016. 2

[19] Michael Janner, Justin Fu, Marvin Zhang, and Sergey Levine. When to trust your model: Model-based policy optimization. arXiv preprint arXiv:1906.08253, 2019. 2

[20] Lukasz Kaiser, Mohammad Babaeizadeh, Piotr Milos, Blazej Osinski, Roy H Campbell, Konrad Czechowski, Dumitru Erhan, Chelsea Finn, Piotr Kozakowski, Sergey Levine, et al. Model-based reinforcement learning for atari. arXiv preprint arXiv:1903.00374, 2019. 2

[21] Peter Karkus, David Hsu, and Woo Sun Lee. QMDP-Net: Deep Learning for Planning under Partial Observability. In I. Guyon, U. V. Luxburg, S. Bengio, H. Wallach, R. Fergus, S. Vishwanathan, and R. Garnett, editors, Advances in Neural Information Processing Systems 30, pages 4694–4704, 2017. 2

[22] Lydia Kavraki, Petr Svestka, J.C. Latombe, and M.H. Overmars. Probabilistic roadmaps for path planning in high-dimensional configuration spaces. IEEE Transactions on Robotics and Automation, 1996. 2

[23] Steven M. Lavalle. Rapidly-exploring random trees: A new tool for path planning. Computer Science Department, Iowa State University, 1998. 2

[24] Steven M. Lavalle and Jr. James J. Kuffner. Rapidly-exploring random trees - progress and prospects. Algorithmic and Computational Robotics: New Directions, 2000. 2

[25] Lisa Lee, Emilio Parisotto, Devendra Singh Chaplot, Eric Xing, and Ruslan Salakhutdinov. Gated Path Planning Networks. arXiv:1806.06408 [cs, stat], June 2018. 2

[26] Daniel James Lenton, Stephen James, Ronald Clark, and Andrew Davison. End-to-end egospheric spatial memory. In International Conference on Learning Representations, 2021. 5

[27] Manolis Savva*, Abhishek Kadian*, Oleksandr Maksymets*, Yili Zhao, Erik Wijmans, Bhavana Jain, Julian Straub, Jia Liu, Vladlen Koltun, Jitendra Malik, Devi Parikh, and Dhruv Batra. Habitat: A Platform for Embodied AI Research. In Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV), 2019. 8

[28] Piotr Mirowski, Razvan Pascanu, Fabio Viola, Hubert Soyer, Andrew J. Ballard, Andrea Banino, Misha Denil, Ross Goroshin, Laurent Sifre, Koray Kavukcuoglu, Dharshan Kumaran, and Raia Hadsell. Learning to Navigate in Complex...
Environments. arXiv:1611.03673 [cs], Jan. 2017. arXiv: 1611.03673. 2

[29] 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 Proceedings of the International Conference on Machine Learning, pages 1928–1937, June 2016. ISSN: 1938-7228 Section: Machine Learning. 1, 2, 3, 4, 5, 6, 7

[30] Raul Mur-Artal and Juan D. Tardos. ORB-SLAM2: an Open-Source SLAM System for Monocular, Stereo and RGB-D Cameras. IEEE Transactions on Robotics, 33(5):1255–1262, Oct. 2017. arXiv: 1610.06475. 5

[31] Andrew Y. Ng and Stuart J. Russell. Algorithms for Inverse Reinforcement Learning. In Proceedings of the International Conference on Machine Learning, ICML ’00, pages 663–670, San Francisco, CA, USA, June 2000. 2

[32] Buqing Nie, Yue Gao, Yidong Mei, and Feng Gao. Capability iteration network for robot path planning. International Journal of Robotics and Automation, 36(0), 2021. 2

[33] Emilio Parisotto and Ruslan Salakhutdinov. Neural map: Structured memory for deep reinforcement learning. arXiv preprint arXiv:1702.08360, 2017. 2

[34] Emilio Parisotto and Ruslan Salakhutdinov. Neural map: Structured memory for deep reinforcement learning. arXiv preprint arXiv:1702.08360, 2017. 2

[35] Stephane Ross, Geoffrey Gordon, and Drew Bagnell. A reduction of imitation learning and structured prediction to no-regret online learning. In Geoffrey Gordon, David Dunson, and Miroslav Dudík, editors, Proceedings of the Fourteenth International Conference on Artificial Intelligence and Statistics, volume 15 of Proceedings of Machine Learning Research, pages 627–635, Fort Lauderdale, FL, USA, 11–13 Apr 2011. PMLR. 2, 3

[36] G A Rummery and M Niranjan. Online Q-learning using Connectionist Systems. Department of Engineering, University of Cambridge, page 21, 1994. 2

[37] Nikolay Savinov, Alexey Dosovitskiy, and Vladlen Koltun. Semi-parametric Topological Memory for Navigation. International Conference on Learning Representations (ICLR), Mar. 2018. 2, 6

[38] Daniel Schleich, Tobias Klamt, and Sven Behnke. Value iteration networks on multiple levels of abstraction. Robotics: Science and Systems XV, Jun 2019. 2

[39] John Schulman, F. Wolski, Prafulla Dhariwal, A. Radford, and O. Klimov. Proximal policy optimization algorithms. ArXiv, abs/1707.06347, 2017. 7

[40] Ali Sharif Razavian, Hossein Azizpour, Josephine Sullivan, and Stefan Carlsson. Cnn features off-the-shelf: an astounding baseline for recognition. In Proceedings of the IEEE conference on computer vision and pattern recognition workshops, pages 806–813, 2014. 1

[41] Anthony Stentz. Optimal and Efficient Path Planning for Partially-Known Environments. In Proceedings of the International Conference on Robotics and Automation, page 8, 1994. 2

[42] Richard S Sutton and Andrew G Barto. Reinforcement Learning: An Introduction. MIT Press, 2nd edition, 2018. 2, 3