Navigation is a rich and well-grounded problem domain that drives progress in many different areas of research: perception, planning, memory, exploration, and optimisation in particular. Historically these challenges have been separately considered and solutions built that rely on stationary datasets—for example, recorded trajectories through an environment. These datasets cannot be used for decision-making and reinforcement learning, however, and in general the perspective of navigation as an interactive learning task, where the actions and behaviours of a learning agent are learned simultaneously with the perception and planning, is relatively unsupported. Thus, existing navigation benchmarks generally rely on static datasets (Geiger et al., 2013; Kendall et al., 2015) or simulators (Beattie et al., 2016; Shah et al., 2018). To support and validate research in end-to-end navigation, we present StreetLearn: an interactive, first-person, partially-observed visual environment that uses Google Street View for its photographic content and broad coverage, and give performance baselines for a challenging goal-driven navigation task. The environment code, baseline agent code, and the dataset are available at http://streetlearn.cc.

Keywords: navigation, environment, reinforcement learning, deep learning, end-to-end

1. Introduction

The subject of navigation is attractive to various research disciplines and technology domains alike, being at once a subject of inquiry from the point of view of neuroscientists wishing to crack the code of grid and place cells (Banino et al., 2018; Cueva and Wei, 2018), as well as a fundamental aspect of robotics research wishing to build mobile robots that can reach a given destination. The majority of navigation algorithms involve building an explicit map during an exploration phase and then planning and acting via that representation. More recently, researchers have sought to directly learn a navigation policy through exploration and interaction with the environment, for instance by using end-to-end deep reinforcement learning (Lample and Chaplot, 2017; Mirowski et al., 2017; Wu et al., 2018; Zhu et al., 2017). To support this research, we have designed an interactive environment called StreetLearn that uses the images and underlying connectivity information from Google Street View (see Fig. 1) in two large areas comprising Pittsburgh and New York City. The environment features high-resolution photographic images displaying a diversity of urban settings, and spans city-scale areas with real-world street connectivity graphs. Within this environment we have developed several traversal tasks that requires the agent navigates from goal to goal over long distances. One such task has a real-world
tasks in Section 2, explain the environment code in Section 3, describe implemented approaches and baseline methods in Section 4 with results in Section 5, and detail related work in Section 6.

2. Environment

This section presents StreetLearn, an interactive environment constructed using Google Street View. Since Street View data has been collected worldwide, and includes both high-resolution imagery and graph connectivity, it is a valuable resource for studying navigation (Fig. 1).

Street View provides a set of geolocated 360° panoramic images which form the nodes of an undirected graph (we use the term node and panorama interchangeably). We selected regions in New York City and Pittsburgh (see Fig. 2). The area of New York City which is available for download is Manhattan south of 81st Street. This comprises approximates 56K panoramic images within a lat/long bounding box defined by (40.695, −74.028) and (40.788, −73.940). Note that Brooklyn, Queens, Roosevelt Island as well as the bridges and tunnels out of Manhattan are excluded, and we include only panoramas inside a polygon that follows the waterfront of Manhattan and 79th / 81st Street, covering an area of 31.6 km². The Pittsburgh dataset comprises 58K images and is defined by a lat/long bounding box between (40.425, −80.035) and (40.460, −79.930), covering an area of 8.9 km by 3.9km. Additionally, we identify three regions in each city which can be used individually for training or for transfer learning experiments. The statistics of each region are given in Table 1.

The undirected graph edges define the proximity and accessibility of nodes to other nodes. We do not reduce or simplify the underlying connectivity but rather use the full graph; thus there are congested areas with many nodes, complex occluded intersections, tunnels and footpaths, and other ephemera. The average node spacing is 10m, with higher densities at intersections. Although the graph is used to construct the environment, the agent never observes the underlying graph—only the RGB images are observed (overlay information, such as arrows, that are visible...
in the public Street View product are also not seen by the agent). Examples of the RGB images and the graph are shown in Figure 1.

In our dataset, each panorama is stored as a Protocol Buffer (Google, 2008) object, containing a string in high-quality compressed JPEG format that encodes the equirectangular image, and decorated with the following attributes: a unique string identifier, the position (lat/long coordinates and altitude in meters) and orientation (pitch, roll and yaw angles) of the panoramic camera, date of acquisition of the image, and a list of directly connected neighbours.

### 2.1. Defining Areas Within the Dataset

The whole Manhattan and Pittsburgh environments in the StreetLearn dataset encompass large urban areas that represent over 56k Street View panoramas each, and traversing these areas from one extremity to another could entail going through close to 1k nodes in the Street View graph. To make learning tractable and also to define distinct regions for training and transfer, one can cut the environment into smaller areas. For instance, Figure 3 illustrates a cut of Manhattan and Pittsburgh into 6 regions ("Wall Street", "Union Square", "Hudson", "CMU", "Allegheny" and "South Shore") that used in our experiments in Section 5.

There are many possibilities to define areas inside a street graph: the most obvious is to cut the graph using a latitude/longitude bounding box, with the disadvantage of creating unconnected components. The second is to cut the graph using a polygon, with the inconvenience of having to specify all the vertices of that polygon, relying on convex hulls to select the nodes included within the polygon. We chose a third approach for defining our areas, by growing graph areas by Breadth-First Search (BFS) (Moore, 1959; Zuse, 1972) from a given node, which requires to choose only a central panorama and a graph depth, and which ensure that the resulting graph is connected. We list in Table 1 the size (in nodes, edges and area coverage), the elevation changes and a description of those areas, including the central panorama ID and the BFS graph depth.

### 2.2. Agent Interface and the Courier Task

An RL environment needs to specify the observations and action space of the agent as well as define the task. The StreetLearn environment provides a visual observation at each timestep, \( x_t \). The visual inputs are meant to simulate a first-person, partially observed environment, thus \( x_t \) is a cropped, 60° square, RGB image that is scaled to \( 84 \times 84 \) pixels (i.e. not the entire panorama).

The action space is composed of five discrete
actions: “slow” rotate left or right (±22.5°), “fast” rotate left or right (±67.5°), or move forward (this action becomes a noop if there is not an edge in view from the current agent pose). If there are multiple edges in the viewing cone of the agent, then the most central one is chosen.

StreetLearn provides an additional observation, the goal descriptor $g_t$, which communicates the task objective to the agent—where to go to receive the next reward. There are many options for how to specify the goal: e.g., images are a natural choice (as in (Zhu et al., 2017)) but quickly become ambiguous at city scale; language-based directions or street addresses could be used (as in (Chen et al., 2018)) though this would place the emphasis on language grounding rather than navigation; and landmarks could be used to encode the target location in a scalable, coordinate-free way (Mirowski et al., 2018). For this courier task we take the simplest route and define goal locations straightforwardly as continuous-valued coordinates $(\text{Lat}_g, \text{Long}_g)$. Note that the goal description is absolute; it is not relative to the agent’s position and only changes when a new goal is drawn (either upon successful goal acquisition or at the beginning of an episode).

In the courier task, which can be summarised as the problem of navigating to a series of random locations in a city, the agent starts each episode from a randomly sampled position and orientation within the StreetLearn graph. A goal location is randomly sampled from the graph and the goal descriptor $g_0$ is computed and input to the agent. If the agent reaches a node that is near to the goal (100m, or approximately one city block), the agent is rewarded and the next goal is randomly chosen and input to the agent. Each episode ends after 1000 agent steps. The reward that the agent gets upon reaching a goal is proportional to the shortest path between the goal and the agent’s position when the goal is first assigned; much like a delivery service, the agent receives a higher reward for longer journeys.

Intuitively, in order to solve the courier task, the agent will need to learn to associate the goal encoding with the images observed at the goal location, as well as to associate the images observed at the current location with the policy to reach different goal locations.

2.3. Curriculum

Curriculum learning gradually increases the complexity of the learning task by choosing more and more difficult examples to present to the learning algorithm (Bengio et al., 2009; Graves et al., 2017; Zaremba and Sutskever, 2014). We have found that a curriculum may be important for the courier task with more distant destinations. Similar to other RL problems such as Montezuma’s Revenge, the courier task suffers from very sparse rewards; unlike that game, we are able to define a natural curriculum scheme. We start by sampling new goals within 500m of the agent’s position (phase 1). In phase 2, we progressively grow the maximum range of allowed goals to cover the full graph.

Note that while this paper focuses on the courier task, but as described in the following Section 3, the environment has been enriched with the possibility of specifying directions through step-by-step pairs of (image, natural language instruction) and goal image.

3. Code

3.1. Code Structure

We have made the environment and agent code available at https://github.com/deepmind/streetlearn. The code repository contains the following components:

- Our C++ StreetLearn engine for loading, caching and serving Google Street View panoramas as well as for handling navigation (moving from one panorama to another) depending on the city street graph and the current position and orientation of the agent. Each panorama is projected from its equirectangular (Wikipedia, 2005) representations to a first-person view for which one can specify the yaw, pitch and field of view angles.
- The message protocol buffers (Google, 2008) used to store the panoramas and the
### The StreetLearn Environment and Dataset

| Region          | #nodes | #edges | av. edge len. | elev. change | area  | description                                                                                       |
|-----------------|--------|--------|---------------|--------------|-------|--------------------------------------------------------------------------------------------------|
| Wall Street     | 7224   | 7496   | 9.8m          | 31m          | 3.8km² | Southernmost area of Manhattan, skyscrapers, narrow streets and highways with irregular intersections. Graph of depth 215, centered at pano 6r1MyYaZ2N4s3T3fFq6G0v. |
| Union Square    | 15525  | 16094  | 9.8m          | 40m          | 9.7km² | Between Downtown and Midtown Manhattan; skyscrapers, brownstones and townhouses; parks and regular street grid. Graph of depth 200, centered at pano dFhp4u7C6vb6y62Axc5g.            |
| Hudson River    | 18085  | 18676  | 9.9m          | 56m          | 11.7km²| Riverside along Hudson River and near Central Park; skyscrapers, regular street grid and highways. Graph of depth 400, centered at pano Fexyv1mG23hnhZz_.zG0v.                         |
| CMU             | 15947  | 16339  | 9.9m          | 146m         | 11.2km²| Suburban areas of Oakland near CMU, suburban, leafy streets with high altitude differentials. Graph of depth 400, centered at pano r5DqC1vcU12Lv6T4Gv0xwq.                                |
| Allegheny       | 14073  | 14567  | 9.8m          | 104m         | 7.2km² | Downtown Pittsburgh and historic district, large avenues, highways and bridges. Graph of depth 320, centered at pano ohvj1xOx3KQPn5PaAMGw.                                  |
| South Shore     | 14967  | 15370  | 9.9m          | 151m         | 9.4km² | Downtown Pittsburgh, South Shore, South Side Flats and Duquesne Heights, highways, bridges and long tunnels, funicular. Graph of depth 350, centered at pano 1jBFHRUoonDeE2om7FPrQ.     |

Table 1 | Relevant information for the three regions in New York (Wall Street, Union Square, and Hudson River) and three regions in Pittsburgh (CMU, Allegheny, and South Shore).

street graph.
- A Python-based interface for calling the StreetLearn environment with custom action spaces.
- Within the Python StreetLearn interface, several games are defined in individual files whose names end with game.py.
- A simple human agent, implemented in Python using Pygame\(^1\), that instantiates the StreetLearn environment on the requested map and enables a user to play the courier or the instruction-following games.
- Oracle agents, similar to the human agent, which automatically navigate towards a specified goal and reports oracle performance on the courier or instruction-following games.
- TensorFlow implementation of agents.

\(^1\)https://www.pygame.org

### 3.2. Code Interface

Our Python StreetLearn environment follows the specifications from OpenAI Gym\(^2\) (Brockman et al., 2016).

After instantiating a specific game and the environment, the environment can be initialised by calling function `reset()` (Note that if the flag `auto_reset` is set to True at construction, `reset()` will be called automatically every time that an episode ends).

As illustrated in Listing 4, the agent plays within the environment by iteratively producing an action, sending it to (stepping through) the environment, and processing the observations and rewards returned by the environment. The call to function `step(action)` returns:

- `observation` (tuple of observations arrays and scalars that are requested at construction),
- `reward` (a floating-point scalar number with the current reward of the agent),
- `done` (boolean indicating whether a game episode has ended and been reset),
- and `info` (a dictionary of environment state variables, which is useful for debugging the

\(^2\)https://gym.openai.com/
agent behaviour or for accessing privileged environment information for visualisation and analysis).

3.3. Actions and observations

We have made four actions available to the agent:

- Rotate left or right in the panorama, by a specified angle (change the yaw of the agent).
- Rotate up or down in the panorama, by a specified angle (change the pitch of the agent).
- Move from current panorama A forward to another panorama B if the current bearing of the agent from A to B is within a tolerance angle of 30 degrees.
- Zoom in and out in the panorama.

As such, agent actions are sent to the environment via \texttt{step(action)} as tuples of 4 scalar numbers. However, for training discrete policy agents via reinforcement learning, action spaces are discretised into integers. For instance, we used 5 actions in (Mirowski et al., 2018): (move forward, turn left by 22.5 deg, turn left by 67.5 deg, turn right by 22.5 deg, turn right by 67.5 deg).

The following observations can currently be requested from the environment:

- \texttt{view_image}: RGB image for the first-person view image returned from the environment and seen by the agent,
- \texttt{graph_image}: RGB image for the top-down street graph image, usually not seen by the agent,
- \texttt{pitch}: Scalar value of the pitch angle of the agent, in degrees (zero corresponds to horizontal),
- \texttt{yaw}: Scalar value of the yaw angle of the agent, in degrees (zero corresponds to North),
- \texttt{yaw_label}: Integer discretized value of the agent yaw using 16 bins,
- \texttt{metadata}: Message protocol buffer of type Pano with the metadata of the current panorama,
- \texttt{target_metadata}: Message protocol buffer of type Pano with the metadata of the target/goal panorama,
- \texttt{latlng}: Tuple of lat/lng scalar values for the current position of the agent,
- \texttt{target_latlng}: Tuple of lat/lng scalar values for the target/goal position,
- \texttt{ground_truth_direction}: Scalar value of the relative ground truth direction to be taken by the agent in order to follow a shortest path to the next goal or waypoint. This observation should be requested only for agents trained using imitation learning.

3.4. Games

The following games are available in the StreetLearn environment:

3.4.1. coin_game

In the coin_game, the rewards consist in invisible coins scattered throughout the map, yielding a reward of 1 for each. Once picked up, these rewards do not reappear until the end of the episode.
3.4.2. courier_game

In the courier_game, the agent is given a goal destination, specified as lat/long pairs. Once the goal is reached (with 100m tolerance), a new goal is sampled, until the end of the episode. Rewards at a goal are proportional to the number of panoramas on the shortest path from the agent’s position when it gets the new goal assignment to that goal position. Additional reward shaping consists in early rewards when the agent gets within a range of 200m of the goal. Additional coins can also be scattered throughout the environment. The proportion of coins, the goal radius and the early reward radius are parameterizable. The curriculum_courier_game is similar to the courier_game, but with a curriculum on the difficulty of the task (maximum straight-line distance from the agent’s position to the goal when it is assigned).

3.4.3. Instruction games

The goal_instruction_game and its variations incremental_instruction_game and step_by_step_instruction_game use navigation instructions to direct agents to a goal. Agents are provided with a list of instructions as well as thumbnails that guide the agent from its starting position to the goal location. In step_by_step, agents are provided one instruction and two thumbnails at a time, in the other game variants the whole list is available throughout the whole game. Reward is granted upon reaching the goal location (all variants), as well as when hitting individual waypoints (incremental and step_by_step only). During training various curriculum strategies are available to the agents, and reward shaping can be employed to provide fractional rewards when the agent gets within a range of 50m of a waypoint or goal.

4. Methods

This section briefly describes the set of approaches which are evaluated on the courier task.

4.1. Goal-dependent Actor-Critic Reinforcement Learning

We formalise the learning problem as a Markov Decision Process, with state space \( S \), action space \( A \), environment \( E \), and a set of possible goals \( G \).

The reward function depends on the current goal and state: \( R : S \times G \times A \rightarrow \mathbb{R} \). The usual reinforcement learning objective is to find the policy that maximises the expected return defined as the sum of discounted rewards starting from state \( s_0 \) with discount \( \gamma \). In this navigation task, the expected return from a state \( s_t \) also depends on the series of sampled goals \( \{g_k\}_k \). The policy is a distribution over actions given the current state \( s_t \) and the goal \( g_t \): \( \pi(a|s,g) = Pr(a_t = a|s_t = s, g_t = g) \). We define the value function to be the expected return for the agent that is sampling actions from policy \( \pi \) from state \( s_t \) with goal \( g_t \):

\[
V^\pi(s,g) = E[R_t] = E\left[\sum_{k=0}^{\infty} \gamma^k r_{t+k}|s_t = s, g_t = g\right].
\]

We hypothesise that an agent should benefit from two types of learning: first, learning a general and location-agnostic representation and exploration behaviour, and second, learning locale-specific structure and features. A navigating agent not only needs an internal representation that is general, to support cognitive processes such as scene understanding, but also needs to organise and remember the features and structures that are unique to a place. Therefore, to support both types of learning, we focus on neural architectures with multiple pathways.

We evaluate two agents on the six regions described in Table 1. We give here a summary of the approach, as the full architectural details of these agents have been previously described (Mirowski et al., 2018). The policy and the value function are both parameterised by a neural network which shares all layers except the final output. The agent operates on raw pixel images \( x_t \), which are passed through a convolutional network as in (Mnih et al., 2016). A Long Short-Term Memory (LSTM) (Hochreiter and Schmidhuber, 1997) receives the output of the convolutional encoder as well as the past reward \( r_{t-1} \) and previous action \( a_{t-1} \). The two different architectures are described below.

The CityNav architecture (Fig. 5b) has a con-
# Instantiate a game (each game has its own class and constructor).

game = courier_game.CourierGame(config)
env = streetlearn.StreetLearn(FLAGS.dataset_path, config, game)
env.reset()
action = np.array([0, 0, 0, 0])
sum_rewards = 0
while True:
    observation, reward, done, info = env.step(action)
    # Plot the observations.
    # [...]  
    # Keep track of episode ends and of rewards.
    sum_rewards += reward
    if done:
        sum_rewards = 0
    # Use info for analysing the agent performance on the game.
    # [...]  
    # Take an action
    action = some_agent_function(observation)

Figure 4 | Main loop for interacting with the environment.

The MultiCityNav architecture (Fig. 5c) extends the CityNav agent to learn in different cities. The remit of the goal LSTM is to encode and encapsulate locale-specific features and topology such that multiple pathways may be added, one per city or region. Moreover, after training on a number of cities, we demonstrate that the convolutional encoder and the policy LSTM become general enough that only a new goal LSTM needs to be trained for new cities.

To train the agents, we use IMPALA (Espeholt et al., 2018), an actor-critic implementation that decouples acting and learning. In our experiments, IMPALA results in similar performance to A3C (Mnih et al., 2016). We use 256 actors for CityNav and 512 actors for MultiCityNav, with batch sizes of 256 or 512 respectively, and sequences are unrolled to length 50.

We note that these computational resources are not available for all, so we have verified that comparable results are attained using only 16 actors and 1 learner, running on a single desktop computer with a Graphics Processing Unit (GPU). The desktop we used had large memory (192 GB) for instantiating 16 StreetLearn environments (each environment requiring a large cache memory for caching panoramas), but smaller memory could be used as well with the trade-off of more
frequent disk accesses.

A TensorFlow implementation of the CityNav and baseline architectures from (Mirowski et al., 2018) is made available on the code repository at https://github.com/deepmind/streetlearn. The trainer code is a directy modification of (Espeholt et al., 2018) from https://github.com/deepmind/scalable_agent and is made available separately.

4.2. Oracle

We also compute an upper bound for all the tasks by computing the shortest path from all panorama positions to the specified goal position using breadth-first search (Moore, 1959; Zuse, 1972) on the panorama connectivity graph. This enables us to calculate both which is the next panorama that agent should go to and the direction that the agent should align with in order to move forward to that panorama, repeating this process until arriving at destination. This ground truth position can be requested as an observation (for imitation learning agents) or be taken from the info dictionary returned by the environment. Listing 6 shows how the oracle agent can be implemented to provide with a valuable measure to benchmark the tasks.

5. Results on the Courier Task

To evaluate the described approaches, we give the individual performance in each region as well as the result of training jointly over multiple regions. We also show the capability of the approach to generalise by evaluating goals in held-out areas, and by training only part of the agent for an entirely new region.

Table 2 gives the average total reward per 1000-step episode achieved by different agents in six different regions of New York City and Pittsburgh defined on Figure 3 and Table 1. Although the agents were trained with reward shaping (i.e., they receive partial rewards when they are within a small radius of the goal), the per-episode returns given here only include the full reward which is given when the goal is reached. The experiments are all replicated with 5 different seeds.

In Table 2, Oracle results are the result of breadth-first search directly on the graph; hence they reflect perfect performance. Single results show the performance of agents trained individually for each region using the CityNav architecture. The trained agents do well in New York City, achieving 85% to 97% of oracle returns, and do less well in Pittsburgh, particularly in the South Shore region where the agent fails completely. This is presumably due to the challenging elevation changes in the region which give rise to convoluted routes even between nearby nodes, and is an artifact of how we specify the curriculum task (based on the maximum Euclidean distance from the agent position to the goal, not accounting for actual travel time). Specifically, when the agent is at the top of Duquesne Hill in South Shore, a goal location on the other side of the river and that is 500m away by bird flight might be kilometres away by road distance.

Joint results show the per-region performance of a MultiCityNav agent that is trained jointly across five regions (South Shore is excluded). The resulting agent suffers only a small drop in performance even though it is now trained across a much broader area: two cities and five regions. Finally, transfer gives the performance of an agent that is trained on four regions (given in italics) and then transferred to a fifth region (Wall Street). In this transfer, only the goal LSTM is modified; there are no gradient updates to the other two components of the architecture (the convolutional encoder or the policy LSTM).

| City               | Oracle | Single | Joint | Transfer |
|--------------------|--------|--------|-------|----------|
| Wall Street        | 809    | 782    | 745   | 541      |
| Union Square       | 750    | 721    | 681   | 667      |
| Hudson River       | 721    | 615    | 621   | 601      |
| CMU                | 755    | 473    | 313   | 355      |
| Allegheny          | 760    | 669    | 571   | 562      |
| South Shore        | 737    | 1      | -     | -        |

Table 2 | Per-city goal rewards for Oracle, single-trained CityNav as well as MultiCityNav agents trained jointly on 5 cities (Wall Street, Union Square and Hudson River in Manhattan, CMU and Allegheny in Pittsburgh) or jointly on 4 cities (Union Square, Hudson River, CMU and Allegheny) then transferred to Wall Street.
game = courier_game.CourierGame(config)
env = streetlearn.StreetLearn(FLAGS.dataset_path, config, game)
env.reset()
action = np.array([0, 0, 0, 0])
action_spec = env.action_spec()
while True:
observation, reward, done, info = env.step(action)
# Plot the observations.
# ...
bearing = info["bearing_to_next_pano"]
if bearing > FLAGS.horizontal_rot:
    action = FLAGS.horizontal_rot * action_spec["horizontal_rotation"]
elif bearing < -FLAGS.horizontal_rot:
    action = -FLAGS.horizontal_rot * action_spec["horizontal_rotation"]
else:
    action = action_spec["move_forward"]

Figure 6 | Oracle implementation using the ground truth direction/bearing to the next panorama.

| Grid size       | Area   | Goal rewards | Fail | \(T_{1/2}\) |
|-----------------|--------|--------------|------|------------|
| No grid         | Train  | 719          | 0%   | 133        |
| Medium grid     | Held-out | 724          | 0%   | 126        |
| Coarse grid     | Held-out | 605          | 2%   | 164        |

Table 3 | CityNav agent generalisation performance (reward and fail metrics) on a set of held-out goal locations (medium and coarse grids). We also compute the half-trip time \(T_{1/2}\), to reach halfway to the goal.

To investigate the generalisation capability of a trained agent, we mask 25% of the possible goals and train on the remaining ones (see Figure 5 in (Mirowski et al., 2018) for an illustration). At test time we evaluate the agent only on its ability to reach goals in the held-out areas. Note that the agent is still able to traverse through these areas, it just never samples a goal there. More precisely, the held-out areas are squares sized 0.01° (coarse grid) or 0.005° (medium grid) of latitude and longitude (respectively roughly about 1km\(^2\) and 0.5km\(^2\)).

In the experiments, we train the CityNav agent for 1B steps, and next freeze the weights of the agent and evaluate its performance on held-out areas for 100M steps. Table 3 shows some decreasing performance of the agents as the held-out area size increases. To gain further understanding, in addition to Test Reward metric, we also use missed goals (Fail) and half-trip time \(T_{1/2}\) metrics. The missed goals metric measures the percentage of times goals were not reached. The half-trip time measures the number of agent steps necessary to cover half the distance separating the agent from the goal.

We also compare, in Table 4, the performance achieved when using (lat, long) goal descriptors versus the previously proposed landmark descriptors (Mirowski et al., 2018). Although the landmark scheme has advantages, such as avoiding fixed coordinate frames, the (lat, long) descriptor is shown to out-perform landmarks on the Union Square region in New York.

| Target representation | Goal rewards |
|-----------------------|--------------|
| Oracle                | 750          |
| (lat, long) scalars   | 721          |
| Landmarks             | 700          |

Table 4 | CityNav agent performance on Union Square with different types of target representations: (lat, long) scalars vs. landmarks.

6. Related Work

The StreetLearn environment is related to a number of other simulators and datasets that have emerged in recent years in response to a greater interest in reinforcement learning and, more generally, learning navigation through interac-
tion. We focus on enumerating these related datasets and environments, referring the reader to Mirowski et al. (2018) for a more complete discussion of related approaches.

Many RL-based approaches for navigation rely on simulators which have the benefit of features like procedurally generated variations but tend to be visually simple and unrealistic, including synthetic 3D environments such as VizDoom (Kempka et al., 2016), DeepMind Lab (Beattie et al., 2016), HoME (Brodeur et al., 2017), House 3D (Wu et al., 2018), Chalet (Yan et al., 2018), or AI2-THOR (Kolve et al., 2017).

To bridge the gap between simulation and reality, researchers have developed more realistic, higher-fidelity simulated environments (Dosovitskiy et al., 2017; Kolve et al., 2017; Shah et al., 2018; Wu et al., 2018). However, in spite of their increasing photo-realism, the inherent problems of simulated environments lie in the limited diversity of the environments and the antiseptic cleanliness of the observations. Our real-world dataset is diverse and visually realistic, comprising scenes with pedestrians, cars, buses or trucks, diverse weather conditions and vegetation and covering large geographic areas. However, we note that there are obvious limitations of our environment: It does not contain dynamic elements, the action space is necessarily discrete as it must jump between panoramas, and the street topology cannot be arbitrarily altered or regenerated.

More visually realistic environments such as Matterport Room-to-Room (Chang et al., 2017), AdobeIndoorNav (Mo et al., 2018), Stanford 2D-3D-S (Armeni et al., 2016), ScanNet (Dai et al., 2017), Gibson Env (Xia et al., 2018), and MINOS (Savva et al., 2017) have been recently introduced to represent indoor scenes, some augmented with navigational instructions.

Using New York imagery, de Vries et al. (2018) use navigation instructions but rely on categorical annotation of nearby landmarks rather than visual observations and use a dataset of 500 panoramas only (ours is two orders of magnitude larger). Very recently, Cirik et al. (2018) and particularly Chen et al. (2018) have also proposed larger datasets of driving instructions grounded in Street View imagery.

7. Conclusion

Navigation is an important cognitive task that enables humans and animals to traverse a complex world without maps. To help understand this cognitive skill, its emergence and robustness, and its application to real-world settings, we have made public a dataset and an interactive environment based on Google Street View. Our carefully curated dataset has been constituted from photographic images that have been manually reviewed and vetted for privacy - we took these extra precautions to ensure that all faces and license plates are blurred appropriately. The dataset is made available at http://streetlearn.cc and is distributed on request; in the case when an individual requests a specific panorama to be taken down or to be blurred on the Google Street View website, we propagate their request to the users of the StreetLearn dataset and provide users with an updated version that complies with the takedown request.

Our environment enables the training of agents to navigate to different goal locations based purely on visual observations and absolute target position representations. We have also expanded that dataset with text instructions to enable reward-based task focused on following relative directions to reach a goal. We will rely on this dataset and environment to address the fundamental problem of grounded, long-range, goal-driven navigation.

Acknowledgements

The authors wish to acknowledge Lasse Espeholt and Hubert Soyer for technical help with the IMPALA algorithm, Razvan Pascanu, Ross Goroshin, Phil Blunsom, and Nando de Freitas for their feedback, Chloe Hillier, Razia Ahamed, Richard Ives and Vishal Maini for help with the project, and the Google Maps and Google Street View teams for their support in accessing the data.
References

Iro Armeni, Ozan Sener, Amir R. Zamir, Helen Jiang, Ioannis Brilakis, Martin Fischer, and Silvio Savarese. 3d semantic parsing of large-scale indoor spaces. In Proceedings of the IEEE International Conference on Computer Vision and Pattern Recognition (CVPR), 2016.

Andrea Banino, Caswell Barry, Benigno Uria, Charles Blundell, Timothy Lillicrap, Piotr Mirowski, Alexander Pritzel, Martin J Chadwick, Thomas DeGriss, Joseph Modayil, Greg Wayne, Hubert Soyer, Fabio Viola, Brian Zhang, Ross Goroshin, Neil Rabinowitz, Razvan Pascanu, Charlie Beattie, Stig Petersen, Amir Sadik, Stephen Gaffney, Helen King, Koray Kavukcuoglu, Demis Hassabis, Raia Hadsell, and Dharshan Kumar. Vector-based navigation using grid-like representations in artificial agents. Nature, 557 (7705):429, 2018.

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.

Joshua Bengio, Jérôme Louradour, Ronan Collobert, and Jason Weston. Curriculum learning. In Proceedings of the 26th annual international conference on machine learning, pages 41–48. ACM, 2009.

Greg Brockman, Vicki Cheung, Ludwig Pettersson, Jonas Schneider, John Schulman, Jie Tang, and Wojciech Zaremba. Openai gym. arXiv preprint arXiv:1606.01540, 2016.

Simon Brodeur, Ethan Perez, Ankes Anand, Florian Golemo, Luca Celotti, Florian Strub, Jean Rouat, Hugo Larochelle, and Aaron Courville. HoME: A household multimodal environment. arXiv preprint arXiv:1711.11017, 2017.

Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Nießner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3d: Learning from RGB-d data in indoor environments. International Conference on 3D Vision (3DV), 2017.

Howard Chen, Alane Shur, Dipendra Misra, Noah Snavely, and Yoav Artzi. Touchdown: Natural language navigation and spatial reasoning in visual street environments. arXiv preprint arXiv:1811.12354, 2018.

Volkan Cirik, Yuan Zhang, and Jason Baldridge. Following formulaic map instructions in a street simulation environment. Visually Grounded Interaction and Language (ViGIL) Workshop, NeurIPS, 2018.

Christopher J Cueva and Xue-Xin Wei. Emergence of grid-like representations by training recurrent neural networks to perform spatial localization. International Conference on Learning Representations, 2018.

Angela Dai, Angel X Chang, Manolis Savva, Maciej Halber, Thomas A Funkhouser, and Matthias Nießner. ScanNet: Richly-annotated 3D reconstructions of indoor scenes. In Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition (CVPR), volume 2, page 10, 2017.

Harm de Vries, Kurt Shuster, Dhruv Batra, Devi Parikh, Jason Weston, and Douwe Kiela. Talk the walk: Navigating New York City through grounded dialogue. arXiv preprint arXiv:1807.03367, 2018.

Alexey Dosovitskiy, German Ros, Felipe Codevilla, Antonio López, and Vladlen Koltun. Carla: An open urban driving simulator. arXiv preprint arXiv:1711.03938, 2017.

Lasse Espeholt, Hubert Soyer, Remi Munos, Karen Simonyan, Volodymir Mnih, Tom Ward, Yotam Doron, Vlad Firoiu, Tim Harlie, Iain Dunn ing, Shane Legg, and Koray Kavukcuoglu. Impala: Scalable distributed deep-rl with importance weighted actor-learner architectures. In International Conference on Machine Learning (ICML), 2018.

Andreas Geiger, Philip Lenz, Christoph Stiller, and Raquel Urtasun. Vision meets robotics: The kitti dataset. The International Journal of Robotics Research, 32(11):1231–1237, 2013.

Google. Protocol Buffers, 2008. URL https: //developers.google.com/protocol-buffers/. (accessed 1 March 2019).

Alex Graves, Marc G Bellemare, Jacob Menick, Remi Munos, and Koray Kavukcuoglu. Automated curriculum learning for neural networks.
In *International Conference on Machine Learning (ICML)*, 2017.

Sepp Hochreiter and Jürgen Schmidhuber. Long short-term memory. *Neural computation*, 9(8): 1735–1780, 1997.

Michał Kempka, Marek Wydmuch, Grzegorz Runc, Jakub Toczek, and Wojciech Jaśkowski. Vizdoom: A doom-based ai research platform for visual reinforcement learning. In *Computational Intelligence and Games (CIG)*, 2016 IEEE Conference on, pages 1–8. IEEE, 2016.

Alex Kendall, Matthew Grimes, and Roberto Cipolla. Posenet: A convolutional network for real-time 6-dof camera relocalization. In *Computer Vision (ICCV)*, 2015 IEEE International Conference on, pages 2938–2946. IEEE, 2015.

Eric Kolve, Roozbeh Mottaghi, Daniel Gordon, Yuke Zhu, Abhinav Gupta, and Ali Farhadi. Ail2or: An interactive 3d environment for visual ai. *arXiv preprint arXiv:1712.05474*, 2017.

Guillaume Lample and Devendra Singh Chaplot. Playing FPS games with deep reinforcement learning. In *Proceedings of the Thirty-First AAAI Conference on Artificial Intelligence*, 2017.

Piotr Mirowski, Razvan Pascanu, Fabio Viola, Hubert Soyer, Andrew J Ballard, Andrea Banino, Misha Denil, Ross Goroshin, Laurent Sifre, Koray Kavukcuoglu, et al. Learning to navigate in complex environments. In *International Conference on Learning Representations (ICLR)*, 2017.

Piotr Mirowski, Matthew Koichi Grimes, Mateusz Malinowski, Karl Moritz Hermann, Keith Anderson, Denis Teplyashin, Karen Simonyan, Koray Kavukcuoglu, Andrew Zisserman, and Raia Hadsell. Learning to navigate in cities without a map. *Advances in Neural Information Processing Systems (NeurIPS)*, 2018.

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.

Kaichun Mo, Haoxiang Li, Zhe Lin, and Joon-Young Lee. The AdobeIndoorNav dataset: Towards deep reinforcement learning based real-world indoor robot visual navigation. *arXiv preprint arXiv:1802.08824*, 2018.

Edward F Moore. The shortest path through a maze. In *Proc. Int. Symp. Switching Theory*, 1959, pages 285–292, 1959.

Manolis Savva, Angel X Chang, Alexey Dosovitskiy, Thomas Funkhouser, and Vladlen Koltun. Minos: Multimodal indoor simulator for navigation in complex environments. *arXiv preprint arXiv:1712.03931*, 2017.

Shital Shah, Debadeepta Dey, Chris Lovett, and Ashish Kapoor. Airsim: High-fidelity visual and physical simulation for autonomous vehicles. In *Field and Service Robotics*, pages 621–635. Springer, 2018.

Wikipedia. *Equirectangular projection*, 2005. URL https://en.wikipedia.org/wiki/Equirectangular_projection. (accessed 1 March 2019).

Yi Wu, Yuxin Wu, Georgia Gkioxari, and Yuandong Tian. Building generalizable agents with a realistic and rich 3d environment. In *European Conference on Computer Vision (ECCV)*, 2018.

Fei Xia, Amir R Zamir, Zhiyang He, Alexander Sax, Jitendra Malik, and Silvio Savarese. Gibson Env: Real-world perception for embodied agents. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, pages 9068–9079, 2018.

Claudia Yan, Dipendra Misra, Andrew Bennnett, Aaron Walsman, Yonatan Bisk, and Yoav Artzi. CHALET: Cornell house agent learning environment. *arXiv preprint arXiv:1801.07357*, 2018.

Wojciech Zaremba and Ilya Sutskever. Learning to execute. *arXiv preprint arXiv:1410.4615*, 2014.

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 *2017 IEEE International Conference on Robotics and Automation, ICRA*, pages 3357–3364, 2017.

Konrad Zuse. *Der Plankalkül*. Number 63. Gesellschaft für Mathematik und Datenverarbeitung, 1972.