Vision-and-Language Navigation: A Survey of Tasks, Methods, and Future Directions

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Abstract

A long-term goal of AI research is to build intelligent agents that can communicate with humans in natural language, perceive the environment, and perform real-world tasks. Vision-and-Language Navigation (VLN) is a fundamental and interdisciplinary research topic towards this goal, and receives increasing attention from the natural language processing, computer vision, and machine learning communities. In this paper, we review contemporary studies in the emerging field of VLN, covering tasks, evaluation metrics, methods, etc. Through structured analysis of current progress and challenges, we also highlight the limitations of current VLN and opportunities for future work. This paper serves as a thorough reference for the VLN research community.

1 Introduction

Humans communicate with each other using natural language to issue tasks and request help. A robot that can understand human language and navigate intelligently would significantly benefit human society, both personally and professionally. Such a robot can be spoken to in natural language, and would autonomously execute tasks such as household chores indoors, repetitive delivery work outdoors, or work in hazardous conditions following human commands (bridge inspection; fire-fighting). Scientifically, developing such a robot explores how an artificial agent interprets natural language from humans, perceives its visual environment, and utilizes that information to execute a sequence of actions to complete a task successfully.

Vision-and-Language Navigation (VLN) (Anderson et al., 2018b; Chen et al., 2019; Thomason et al., 2019b) is an emerging research field that aims to build such an embodied agent that can communicate with humans in natural language and navigate in real 3D environments. VLN extends visual navigation in both simulated (Zhu et al., 2017; Mirowski, 2019) and real environments (Mirowski et al., 2018) with natural language communication. As illustrated in Figure 1, VLN is a task that involves the oracle (frequently a human), the robot agent, and the environment. The agent and the oracle communicate in natural language. The agent may ask for guidance and the oracle could respond. The agent navigates and interacts with the environment to complete the task according to the instructions received and the environment observed. Meanwhile, the oracle observes the environment and agent status, and may interact with the environment to help the agent.

Since the development and release of Room-to-Room (R2R) (Anderson et al., 2018b), many VLN datasets have been introduced. Regarding the degree of communication, researchers create benchmarks where the agent is required to passively understand one instruction before navigation, to benchmarks where agents converse with the oracle in free-form dialog. Regarding the task objective, the requirements for the agent range from strictly following the route described in the initial
instruction, to actively exploring the environment and interacting with objects.

Many challenges exist in VLN tasks. First, VLN faces a complex environment and requires effective understanding and alignment of information from different modalities. Second, VLN agents require a reasoning strategy for the navigation process. Data scarcity is also an obstacle. Lastly, the generalization of a model trained in seen environments to unseen environments is also essential. We categorize the solutions according to the respective challenges. (1) Representation learning methods help understand information from different modalities. (2) Action strategy learning aims to make reasonable decisions based on gathered information. (3) Data-centric learning methods effectively utilize the data and address data challenges such as data scarcity. (4) Prior exploration helps the model familiarize itself with the test environment, improving its ability to generalize.

We make three primary contributions. (1) We systematically categorize current VLN benchmarks from communication complexity and task objective perspectives, with each category focusing on a different type of VLN task. (2) We hierarchically classify current solutions and the papers within the scope. (3) We discuss potential opportunities and identify future directions.

2 Tasks and Datasets

The ability for an agent to interpret natural language instructions (and in some instances, request feedback during navigation) is what makes VLN unique from visual navigation (Bonin-Font et al., 2008). In Table 2, we mainly categorize current datasets on two axes, Communication Complexity and Task Objective.

Communication Complexity defines the level at which the agent may converse with the oracle, and we differentiate three levels: In the first level, the agent is only required to understand an Initial Instruction before navigation starts. In the second level, the agent sends a signal for help whenever it is unsure, utilizing the Guidance from the oracle. In the third level, the agent with Dialog ability asks questions in the form of natural language during the navigation and understands further oracle guidance.

Task Objective defines how the agent attains its goal. In the first objective type, Fine-grained Navigation, the agent can find the target according to a detailed step-by-step route description. In the second type, Course-grained Navigation, the agent is required to find a distant target goal with a coarse navigation description, requiring the agent to reason a path in an unseen environment. Tasks in the previous two types only require the agent to navigate to complete the mission. In the third type, Navigation and Object Interaction, besides reasoning a path, the agent also needs to interact with objects in the environment to achieve the goal since the object might be hidden or need to change physical states.¹

2.1 Initial Instruction

Currently, in the setting of many benchmarks, the agent is given a natural language instruction for the whole navigation process, such as “Go upstairs and pass the table in the living room. Turn left and go through the door in the middle.”

Fine-grained Navigation An agent needs to strictly follow the natural language instruction to reach the target goal. Anderson et al. (2018b) create R2R dataset and build the Matterport3D simulator. An embodied agent in R2R moves through a house in the simulator traversing edges on a navigation graph, jumping to adjacent nodes containing panoramic views. R2R is extended to create other VLN benchmarks. Room-for-Room joins paths in R2R to longer trajectories (Jain et al., 2019). Yan et al. (2020) collect XL-R2R to extend R2R with Chinese instructions. RxR (Ku et al., 2020) contains instructions from English, Hindi, Telugu. The dataset has more samples and the instructions in it are time-aligned to the virtual poses of the instruction. The English split of RxR is further extended to build Landmark-RxR (He et al., 2021) by incorporating landmark information.

In most current datasets, agents traverse a navigation graph at predefined viewpoints. To facilitate transfer learning to real robots, VLN tasks should provide a continuous action space and a freely navigable environment. To this end, Krantz et al. (2020) reconstruct the navigation graph based R2R trajectories in continuous environments and create VLNCE. Irshad et al. (2021) propose Robo-VLN task where the agent operates in a continuous action space over long-horizon trajectories.

Outdoor environments are usually more com-

¹Navigation and Object Interaction includes both fine-grained and coarse-grained instructions, which ideally should be split further. But given that there are only few datasets in this category, we keep the current categorization in Table 2.
Table 1: Vision-and-Language Navigation datasets organized by Communication Complexity versus Task Objective. Please refer to Appendix for more details about the datasets and the commonly used underlying simulators.
find objects. The agent could request help from the oracle, which responds by providing a subtask which helps the agent make progress. While oracle in VNL uses predefined script to respond, the oracle in HANNA uses a neural network to generate natural language responses.

**Navigation+Object Interaction** While VLN is still in its youth, there are no VLN datasets in support of Guidance and Object Interaction.

### 2.3 Dialog

It is human-friendly to use natural language to request help (Banerjee et al., 2020; Thomason et al., 2019b). For example, when agent is not sure about what fruit the human wants, it could ask “What fruit do you want, the banana in the refrigerator or the apple on the table?”, and the human response would provide clear direction.

**Fine-grained Navigation** No datasets are in the scope of this category. Currently, route-detailed instruction with possible guidance could help the agent achieve relatively good performance in most simulated environments. We expect datasets to be developed for this category for complex environments especially with rich dynamics where dialog is necessary to clear confusions.

**Coarse-grained Navigation** CVDN (Thomason et al., 2019b) is a dataset of human-human dialogues. Besides interpreting a natural language instruction and deciding on the following action, the VLN agent also needs to ask questions in natural language for guidance. The oracle, with knowledge of the best next steps, needs to understand and correctly answer said questions. CEREALBAR (Suhr et al., 2019) is a collaborative task between a leader and a follower. Both agents move in a virtual game environment to collect valid sets of cards.

Dialog is important in complex outdoor environments. de Vries et al. (2018) introduce the Talk the Walk dataset, where the guide has knowledge from a map and guides the tourist to a destination, but does not know the tourist’s location; while the tourist navigates a 2D grid via discrete actions.

**Navigation+Object Interaction** Minecraft Collaborative Building (Narayan-Chen et al., 2019) studies how an agent places blocks into a building by communicating with the oracle. TEACh (Padmukumar et al., 2021) is a dataset that studies object interaction and navigation with free-form dialog. The follower converses with the commander and interacts with the environment to complete various house tasks such as making coffee.

### 3 Evaluation

**Goal-oriented Metrics** mainly consider the agent’s proximity to the goal. The most intuitive is Success Rate (SR), which measures how frequently an agent completes the task within a certain distance of the goal. Goal Progress (Thomason et al., 2019b) measures the reduction in remaining distance to the target goal. Path Length (PL) measures the total length of the navigation path. Shortest-Path Distance (SPD) measures the mean distance between the agent’s final location and the goal. Since a longer path length is undesirable (increases duration and wear-and-tear on actual robots), Success weighted by Path Length (SPL) (Anderson et al., 2018a) balances both Success Rate and Path Length. Similarly, Success weighted by Edit Distance (SED) (Chen et al., 2019) compares the expert’s actions/trajectory to the agent’s actions/trajectory, also balancing SR and PL. Oracle Navigation Error (ONE) takes the shortest distance from any node in the path rather than just the last node, and Oracle Success Rate (OSR) measures whether any node in the path is within a threshold from the target location.

**Path-fidelity Metrics** evaluate to what extent an agent follows the desired path. The fidelity between the instruction and the path is important when evaluating an agent’s performance. Coverage weighted by LS (CLS) (Jain et al., 2019) is the product of the Path Coverage (PC) and Length Score (LS) with respect to the reference path. It measures how closely an agent’s trajectory follows the reference path. Normalized Dynamic Time Warping (nDTW) (Ilharco et al., 2019) softly penalizes deviations from the reference path to calculate the match between two paths. Success weighted by normalized Dynamic Time Warping (SDTW) (Ilharco et al., 2019) further constrains nDTW to only successful episodes to capture both success and fidelity.

### 4 VLN Methods

As shown in Figure 2, we categorize existing methods into Representation Learning, Action Strategy Learning, Data-centric Learning, and Prior Exploration. Representation learning methods help agent understand relations between these modalities since VLN involves multiple modalities, including vision, language, and action. Moreover, VLN is a complex reasoning task where mission re-
sults depend on the accumulating steps, and better action strategies help the decision-making process. Additionally, VLN tasks face challenges within their training data. One severe problem is scarcity. Collecting training data for VLN is expensive and time-consuming, and the existing VLN datasets are relatively small with respect to the complexity of VLN tasks. Therefore, data-centric methods help to utilize the existing data and create more training data. Prior exploration helps adapt agents to previously unseen environments, improving their ability to generalize, decreasing the performance gap between seen versus unseen environments.

4.1 Representation Learning

Representation learning helps the agent understand how the words in the instruction relate to the perceived features in the environment.

4.1.1 Pretraining

**Vision or Language** Using a pretrained model to initialize a vision or text encoder provides agents with single-modality knowledge. pretrained vision models may use a ResNet (He et al., 2016) or Vision Transformers (Dosovitskiy et al., 2020). Other navigation tasks (Wijmans et al., 2019b) may also provide visual initialization (Krantz et al., 2020). Large pretrained language models such as BERT (Devlin et al., 2019) and GPT (Radford et al., 2019) can encode language and improve instruction understanding (Li et al., 2019), which can be further pretrained with VLN instructions (Pashevich et al., 2021) before fine-tuning in VLN task.

**Vision and Language** Vision-and-language pretrained models provide good joint representation for text and vision. A common practice is to initialize the VLN agent with a pretrained model such as ViLBERT (Lu et al., 2019). The agent may be further trained with VLN-specific features such as objects and rooms (Qi et al., 2021).

**VLN** Downstream tasks benefit from being closely related to the pretraining task. Researchers also explored pretraining on the VLN domain directly. VLN-BERT (Majumdar et al., 2020) pretrains navigation models to measure the compatibility between paths and instructions. PREVALENT (Hao et al., 2020) is trained from scratch on image-text-action triplets to learn textual representations in VLN tasks. The [CLS] token in BERT-based pretraining models could be leveraged in a recurrent fashion to represent history state (Hong et al., 2021; Moudgil et al., 2021). Airbert (Guhur et al., 2021) achieve good performance on few-shot setting after pretraining on a large-scale in-domain dataset.

4.1.2 Semantic Understanding

Semantic understanding of VLN tasks incorporates knowledge about important features in VLN. In addition to the raw features, high-level semantic representations also improve performance.

**Intra-Modality** Visual or textual modalities can be decomposed into many features, which matter differently in VLN. The overall visual features extracted by a neural model may actually hurt the performance in some cases (Thomason et al., 2019a; Hu et al., 2019; Zhang et al., 2020b). Therefore, it is important to find the feature(s) that best improve performance. High-level features such as visual appearance, route structure, and detected objects outperform the low level visual features extracted by CNN (Hu et al., 2019). Different types of tokens within the instruction also function differently (Zhu et al., 2021b). Extracting these tokens and encoding the object tokens and directions tokens are crucial (Qi et al., 2020a; Zhu et al., 2021b).

**Inter-Modality** Semantic connections between different modalities: actions, scenes, observed objects, direction clues, and objects mentioned in instructions can be extracted and then softly aligned with attention mechanism (Qi et al., 2020a; Gao et al., 2021). The soft alignment also highlights relevant parts of the instruction with respect to the cur-
rent step (Landi et al., 2019; Zhang et al., 2020a).

4.1.3 Graph Representation
Graph has been widely applied to model relationships. Building graph to incorporate structured information from instruction and observation provides explicit semantic relation to guide the navigation. The graph neural network may encode the relation between text and vision to better interpret the context information (Hong et al., 2020a). The graph could record the location information during the navigation, which can be used to predict the most likely trajectory (Anderson et al., 2019a) or probability distribution over action space (Deng et al., 2020). When connected with prior exploration, an overview graph about the navigable environment (Chen et al., 2021a) can be built to improve navigation interpretation.

4.1.4 Memory-augmented Model
Information accumulates as the agent navigates, which is not efficient to utilize directly. Memory structure helps the agent effectively leverage the navigation history. Some solutions leverage memory modules such as LSTMs or recurrently utilize informative states (Hong et al., 2021), which can be relatively easily implemented, but may struggle to remember features at the beginning of the path as path length increases. Another solution is to build a separate memory model to store the relevant information (Zhu et al., 2020c; Lin et al., 2021; Nguyen and Daumé III, 2019). Notably, by hierarchically encoding a single view, a panorama, and then all panoramas in history, HAMT (Chen et al., 2021b) successfully utilized the full navigation history for decision-making.

4.1.5 Auxiliary Tasks
Auxiliary tasks help the agent better understand the environment and its own status without extra labels. From the machine learning perspective, an auxiliary task is usually achieved in the form of an additional loss function. The auxiliary task could, for example, explain its previous actions, or predict information about future decisions (Zhu et al., 2020a). Auxiliary tasks could also involve the current mission such as current task accomplishment, and vision instruction alignment (Ma et al., 2019a; Zhu et al., 2020a). Notably, auxiliary tasks are effective when adapting pretrained representations into the VLN domain (Huang et al., 2019).

4.2 Action Strategy Learning
With a variety of possible action sequences, action strategy learning provides a variety of methods to help the agent decide on those best actions.

4.2.1 Reinforcement Learning
VLN is a sequential decision-making problem and can naturally be modeled as a Markov decision process. So Reinforcement Learning (RL) methods are proposed to learn better policy for VLN tasks. A critical challenge for RL methods is that VLN agents only receive the success signal at the end of the episode, so it is difficult to know which actions to attribute success to, and which to penalize. To address the ill-posed feedback issue, Wang et al. (2019) propose RCM model to enforces cross-modal grounding both locally and globally, with goal-oriented extrinsic reward and instruction-fidelity intrinsic reward. He et al. (2021) propose to utilize the local alignment between the instruction and critical landmarks as the reward. Evaluation metrics such as CLS (Jain et al., 2019) or nDTW (Ilharco et al., 2019) can also provide informative reward signal (Landi et al., 2020).

To model rich dynamics in the environment, Wang et al. (2018) leverage model-based reinforcement learning to predict the next state and improve the generalization in unseen environment. Zhang et al. (2020a) find recursively alternating the learning schemes of imitation and reinforcement learning improve the performance.

4.2.2 Exploration during Navigation
Exploring and gathering environmental information while navigating provides a better understanding of the state space. Student-forcing is a frequently used strategy, where the agent keeps navigating based on sampled actions and is supervised by the shortest-path action (Anderson et al., 2018b).

There is a tradeoff between exploration versus exploitation: with more exploration, the agent sees better performance at the cost of a longer path and longer duration, so the model needs to determine when and how deep to explore (Wang et al., 2020a). After having gathered the local information, the agent needs to decide which step to choose, or whether to backtrack (Ke et al., 2019). Notably, Koh et al. (2021) designed Pathdreamer, a visual world model to synthesize visual observation future viewpoints without actually looking ahead.
4.2.3 Navigation Planning

Planning future navigation steps leads to a better action strategy. From the visual side, predicting the waypoints (Krantz et al., 2021), next state and reward (Wang et al., 2018), generate future observation (Koh et al., 2021) or incorporating neighbor views (An et al., 2021) has proven effective. The natural language instruction also contains landmarks and direction clues to plan detailed steps. Anderson et al. (2019b) predict the forthcoming events based on the instruction, which is used to predict actions with a semantic spatial map.

4.2.4 Asking for Help

An intelligent agent asks for help when uncertain about the next action. Action probabilities or a separately trained model (Chi et al., 2020; Zhu et al., 2021c; Nguyen et al., 2021) can be leveraged to decide whether to ask for help. Using natural language to converse with the oracle covers a wider problem scope than sending a signal. Both rule-based methods (Padmakumar et al., 2021) and neural-based methods (Roman et al., 2020; Nguyen et al., 2021) have been developed to build navigation agents with dialog ability. Meanwhile, for tasks (Thomason et al., 2019b; Padmakumar et al., 2021) that do not provide an oracle agent to answer question in natural language, researchers also need to build a rule-based (Padmakumar et al., 2021) or neural-based (Roman et al., 2020) oracle.

4.3 Data-centric Learning

Compared with previously discussed works that focus on building a better VLN agent structure, data-centric methods most effectively utilize the existing data, or create synthetic data.

4.3.1 Data Augmentation

Trajectory-Instruction Augmentation Augmented path-instruction pairs could be used in VLN directly. Currently the common practice is to train a speaker module to generate instructions given a navigation path (Fried et al., 2018). This generated data could have varying quality (Zhao et al., 2021). Therefore an alignment scorer (Huang et al., 2019) or adversarial discriminator (Fu et al., 2020) can select high-quality pairs for augmentation.

Environment Augmentation Generating more environment data not only helps generate more trajectories, but also alleviates the problem of overfitting in seen environments. Randomly masking the same visual feature across different viewpoints (Tan et al., 2019) or simply splitting the house scenes and remixing them (Liu et al., 2021) could create new environments, which could further be used to generate more trajectory-instruction pairs (Fried et al., 2018). Training data may also be augmented by replacing some visual features with counterfactual ones (Parvaneh et al., 2020).

4.3.2 Curriculum Learning

Curriculum learning (Bengio et al., 2009) gradually increases the task’s difficulty during the training process. The instruction length could be a metric for task difficulty. BabyWalk (Zhu et al., 2020b) keep increasing training samples’ instruction length during the training process. Attributes from the trajectory may also be used to rank task difficulty. Zhang et al. (2021) rearrange the R2R dataset using the number of rooms each path traverses. They found curriculum learning helps smooth the loss landscape and find a better local optima.

4.3.3 Multitask Learning

Different VLN tasks can learn from each other by cross-task knowledge transfer. Wang et al. (2020c) propose an environment-agnostic multitask navigation model for both VLN and Navigation from Dialog History tasks (Thomason et al., 2019b). Chaplot et al. (2020) propose an attention module to train a multitask navigation agent to follow instructions and answer questions (Wijmans et al., 2019a).

4.3.4 Instruction Interpretation

A trajectory instruction phrased multiple times in different ways may help the agent better understand its objective. LEO (Xia et al., 2020) leverages and encodes all the instructions with a shared set of parameters to enhance the textual understanding. Shorter, and more concise instructions provide clearer guidance for the agent compared to longer, semantically entangled instructions, thus Hong et al. (2020b) breaks long instructions into shorter ones, allowing the agent to track progress and focus on each atomic instruction individually.

4.4 Prior Exploration

Good performance in seen environments often cannot generalize to unseen environments (Parvaneh et al., 2020; Tan et al., 2019). Prior exploration methods allow the agent to observe and adapt to unseen environments\(^2\), bridging the performance

\(^2\)Thus prior exploration methods are not directly comparable with other VLN methods.
5 Conclusion and Future Directions

In this paper, we discuss the importance of VLN agents as a part of society, how their tasks vary as a function of communication level versus task objective, and how different agents may be evaluated. We broadly review VLN methodologies and categorize them. This paper only discusses these issues broadly at an introductory level. In reviewing these papers, we can see the immense progress that has already been made, as well as directions that this research topic can be expanded on.

Current methods usually do not explicitly utilize external knowledge such as objects and house descriptions in Wikipedia. Incorporating knowledge also improves the interpretability and trust of embodied AI. Moreover, currently several navigation agents learn which direction to move and with what to interact, but there is a last-mile problem of VLN—how to interact with objects. Anderson et al. (2018b) asked whether a robot could learn to “Bring me a spoon”; new research may ask how a robot can learn to “Pick up a spoon”. The environments also lack diversity: most interior terrestrial VLN data consists of American houses, but never warehouses or hospitals: the places where these agents may be of most use.

Below we detail additional future directions:

**Collaborative VLN** Current VLN benchmarks and methods predominantly focus on tasks where only one agent navigates, yet complicated real-world scenarios may require several robots collaborating. Multi-agent VLN tasks require development in swarm intelligence, information communication, and performance evaluation. VLN studies the relationship between the human and the environment in Figure 1, yet here humans are oracles simply observing (but not acting on) the environment. Collaboration between humans and robots is crucial for them to work together as teams (e.g., as personal assistants or helping in construction). Future work may target at collaborative VLN between multiple agents or between human and agents.

**Simulation to Reality** There is a performance loss when transferred to real-life robot navigation (Anderson et al., 2020). Real robots function in continuous space, but most simulators only allow agents to “hop” through a pre-defined navigation graph which is unrealistic for three reasons (Krantz et al., 2020). Navigation graphs assume: (1) perfect localization—in the real world is a noisy estimate; (2) oracle navigation—real robots cannot “teleport” to a new node; (3) known topology—in reality an agent may not have access to a preset list of navigable nodes. Continuous implementations of realistic environments may contain patches of the images, be blurred, or have parallax errors, making them unrealistic. A simulation that is based on both a 3D model and realistic imagery could improve the match between virtual sensors (in simulation) and real sensors. Lastly, most simulators assume a static environment only changed by the agent. This does not account for other dynamics such as people walking or objects moving, nor does it account for lighting conditions through the day. VLN environments with probabilistic transition function may also narrow the gap between simulation and reality.

**Ethics & Privacy** During both training and inference, VLN agents may observe and store sensitive information that can get leaked or misused. Effective navigation with privacy protection is crucially important. Relevant areas such as federated learning (Konečný et al., 2016) or differential privacy (Dwork et al., 2006) could also be studied in VLN domain to preserve the privacy of training and inference environments.

**Multicultural VLN** VLN lacks diversity in 3D environments: most outdoor VLN datasets use Google Street View recorded in major American cities, but lacks data in developing countries. Agents trained on American data face potential generalization problems in other city or housing layouts. Future work should explore more diverse environments across multiple cultures and regions. Multilingual VLN datasets (Ku et al., 2020; Yan et al., 2020) could be good resources to study multicultural differences from the linguistic perspective.
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A Dataset Details

Here in Table 2, we introduce more information about the datasets. Compared with the number of the datasets, the simulators are limited. More specifically, most indoor datasets are based on Matterport3D and most outdoor datasets are based on Google Street View. Also, more datasets are about indoor environments rather than outdoor environments. Outdoor environments are usually more complex and contain more objects compared with indoor environments.

B Simulator

The virtual features of the dataset are deeply connected with the simulator in which datasets are built. Here we summarize simulators frequently used during the VLN dataset creation process.

House3D (Wu et al., 2018) is a realistic virtual 3D environment built based on the SUNCG (Song et al., 2017) dataset. An agent in the environment has access to first-person view RGB images, together with semantic/instance masks and depth information.

Matterport3D (Anderson et al., 2018b) simulator is a large-scale visual reinforcement learning simulation environment for research on embodied AI based on the Matterport3D dataset (Chang et al., 2017). Matterport3D contains various indoor scenes, including houses, apartments, hotels, offices, and churches. An agent can navigate between viewpoints along a pre-defined graph. Most indoors VLN datasets such as R2R and its variants are based on the Matterport3D simulator.

Habitat (Manolis Savva* et al., 2019; Szot et al., 2021) is a 3D simulation platform for training embodied AI in 3D physics-enabled scenarios. Compared with other simulation environments, Habitat 2.0 (Szot et al., 2021) shows strength in system response speed. Habitat has the following datasets built-in: Matterport3D (Chang et al., 2017), Gibson (Xia et al., 2018), and Replica (Straub et al., 2019). AI2-THOR (Kolve et al., 2017) is a near photo-realistic 3D indoor simulation environment, where agents could navigate and interact with objects. Based on the object interaction function, it helps to build a dataset that requires object interaction, such as ALFRED (Shridhar et al., 2020).

Gibson (Xia et al., 2018) is a real-world perception interactive environment with complex semantics. Each viewpoint has a set of RGB panoramas with global camera poses and reconstructed 3D meshes. Matterport3D dataset (Chang et al., 2017) is also integrated into the Gibson simulator.

House3D (Wu et al., 2018) converts SUNCG’s static environment into a virtual environment, where the agent can navigate with physical constraints (e.g. it cannot pass through walls or objects).

LANI (Misra et al., 2018) is a 3D simulator built in Unity3D platform. The environment in LANI is a fenced, square, grass field containing randomly placed landmarks. An agent needs to navigate between landmarks following the natural language instruction. Drone navigation tasks (Blukis et al., 2018, 2019) are also built based on LANI.

Currently, most datasets and simulators focus on indoors navigable scenes partly because of the difficulty of building an outdoor photo-realistic 3D simulator out of the increased complexity. Google Street View, an online API that is integrated with Google Maps, is composed of billions of realistic street-level panoramas. It has been frequently used to create outdoor VLN tasks since the development of TOUCHDOWN (Chen et al., 2019).

C Room-to-Room Leaderboard

Room-to-Room (R2R) (Anderson et al., 2018b) is the benchmark used most frequently for evaluating different methods. Here we collect all the reported performance metrics in the corresponding papers and the official R2R leaderboard. Since beam search explores more routes, and since prior exploration has additional observations in the test environment, their performance can not be directly compared with other methods.
| Name                      | Simulator | Language-Active | Environment |
|---------------------------|-----------|----------------|-------------|
| Room-to-Room (Anderson et al., 2018b) | Matterport3D | ❌ | Indoor |
| Room-for-Room (Jain et al., 2019)      | Matterport3D | ❌ | Indoor |
| Room-Across-Room (Ku et al., 2020)     | Matterport3D | ❌ | Indoor |
| Landmark-RxR (He et al., 2021)         | Matterport3D | ❌ | Indoor |
| XL-R2R (Yan et al., 2020)              | Matterport3D | ❌ | Indoor |
| VLNCE (Krantz et al., 2020)            | Habitat    | ❌ | Indoor |
| StreetLearn (Mirowski et al., 2019)    | Google Street View | ❌ | Outdoor |
| StreetNav (Hermann et al., 2020)       | Google Street View | ❌ | Outdoor |
| TOUCHDOWN (Chen et al., 2019)          | Google Street View | ❌ | Outdoor |
| Talk2Nav (Vasudevan et al., 2021)      | Google Street View | ❌ | Outdoor |
| RoomNav (Wu et al., 2018)              | House3D    | ❌ | Indoor |
| REVERIE (Qi et al., 2020b)             | Matterport3D | ❌ | Indoor |
| SOON (Zhu et al., 2021a)               | Matterport3D | ❌ | Indoor |
| ALFRED (Shridhar et al., 2020)         | AI2-THOR   | ❌ | Indoor |
| VNLNA (Misra et al., 2018)             | Matterport3D | ✓ | Indoor |
| HANNA (Nguyen and Daumé III, 2019)     | Matterport3D | ✓ | Indoor |
| CEREALBAR (Suhr et al., 2019)          | -          | ✓ | Indoor |
| Just Ask (Chi et al., 2020)            | Matterport3D | ✓ | Indoor |
| CVDN (Thomason et al., 2019b)          | Matterport3D | ✓ | Indoor |
| RobotSlang (Banerjee et al., 2020)     | -          | ✓ | Indoor |
| Talk the Walk (de Vries et al., 2018)  | -          | ✓ | Outdoor |
| MC Collab (Narayan-Chen et al., 2019)  | Minecraft | ✓ | Outdoor |
| TEACH (Padmakumar et al., 2021)        | AI2-THOR   | ✓ | Indoor |

Table 2: Vision-and-Language Navigation datasets. Language-Active means the agent needs to use natural language to request help, including both Guidance datasets and Dialog datasets in Table 1.

| Simulator              | Photo-realistic | 3D |
|------------------------|-----------------|----|
| House3D (Wu et al., 2018) | ✓              | ✓  |
| Matterport3D (Chang et al., 2017) | ✓          | ✓  |
| Habitat (Manolis Savva* et al., 2019) | ✓          | ✓  |
| AI2-THOR (Kolve et al., 2017) | ❌          | ✓  |
| Gibson (Xia et al., 2018)   | ✓              | ✓  |
| LANI (Misra et al., 2018)   | ❌              | ✓  |
| *Google Street View        | ✓              | ✓  |

Table 3: Common simulators used to build VLN datasets. *Google Street View is online API, providing similar functionality as a simulator for building VLN datasets.
| Models                              | Single Run | Prior Exploration | Beam Search |
|------------------------------------|------------|-------------------|-------------|
| Leader-Board (Test Unseen)         |            |                   |             |
| Random                             | 0.95       | 6.10              | -           |
| Human                              | 11.85      | 1.61              | 0.86        |
| Seq-to-Seq (Anderson et al., 2018b)| 8.13       | 40.3              | 0.20        |
| TL                                  | -          | -                 | -           |
| NE                                 | -          | -                 | -           |
| OSR                                | -          | -                 | -           |
| SR                                 | -          | -                 | -           |
| SPL                                | -          | -                 | -           |
| Random                             | 9.89       | 9.79              | 0.18        |
| Human                              | 11.85      | 1.61              | 0.86        |
| Seq-to-Seq (Anderson et al., 2018b)| 8.13       | 40.3              | 0.20        |
| TL                                  | -          | -                 | -           |
| NE                                 | -          | -                 | -           |
| OSR                                | -          | -                 | -           |
| SR                                 | -          | -                 | -           |
| SPL                                | -          | -                 | -           |
| Random                             | 9.89       | 9.79              | 0.18        |
| Human                              | 11.85      | 1.61              | 0.86        |
| Seq-to-Seq (Anderson et al., 2018b)| 8.13       | 40.3              | 0.20        |
| TL                                  | -          | -                 | -           |
| NE                                 | -          | -                 | -           |
| OSR                                | -          | -                 | -           |
| SR                                 | -          | -                 | -           |
| SPL                                | -          | -                 | -           |
| Random                             | 9.89       | 9.79              | 0.18        |
| Human                              | 11.85      | 1.61              | 0.86        |
| Seq-to-Seq (Anderson et al., 2018b)| 8.13       | 40.3              | 0.20        |
| TL                                  | -          | -                 | -           |
| NE                                 | -          | -                 | -           |
| OSR                                | -          | -                 | -           |
| SR                                 | -          | -                 | -           |
| SPL                                | -          | -                 | -           |

Table 4: Leaderboard of Room-to-Room benchmark as of November, 2021.