Visual-and-Language Navigation: A Survey and Taxonomy

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Abstract—An agent that can understand natural-language instruction and carry out corresponding actions in the visual world is one of the long-term challenges of Artificial Intelligent (AI). Due to multifarious instructions from humans, it requires the agent can combine natural language to vision and action in unstructured, previously unseen environments. If the instruction given by human is a navigation task, this challenge is called Visual-and-Language Navigation (VLN). It is a booming multi-disciplinary field of increasing importance and with extraordinary practicality. Instead of focusing on the details of specific methods, this paper provides a comprehensive survey on VLN tasks and makes a classification carefully according the different characteristics of language instructions in these tasks. According to when the instructions are given, the tasks can be divided into single-turn and multi-turn. For single-turn tasks, we further divided them into goal-orientation and route-orientation based on whether the instructions contain a route. For multi-turn tasks, we divided them into imperative task and interactive task based on whether the agent responses to the instructions. This taxonomy enable researchers to better grasp the key point of a specific task and identify directions for future research.

Index Terms—Visual-and-Language Navigation, Survey, Taxonomy.

I. INTRODUCTION

Imaging you are going to attend a meeting in a place where you had never visited. With the help of GPS and digital map, it is easy to plan a route to cover 99% distance to the final goal. However, we may get lost even only one kilometer left. At this time, we may make a call to the host or turn to a passerby, she/he will guide you with some language instructions. The instructions may contain some directional guide and some visual landmarks. With the help, you can get to the meeting place.

Vision and Language Navigation (VLN) [1] is the very task to linking natural language to vision and navigation in unstructured, unseen environments. It has driven increasing interest from researchers in both the Computer Vision (CV) and Natural Language Processing (NLP) fields.

Significant process have been made in some tasks both in CV and NLP fields due to the success of deep learning. This surge firstly occurred in some tasks of CV such as classification [2], detection [3], segmentation [4], etc., using self-supervision [5] or large annotated datasets.

In the following, NLP has achieved prominent improvements in solving multi-task with pre-trained language model as backbone [6, 7], which has been trained on large unlabeled corpora.

Meanwhile, Lee et al. [8] had proved that using a neural network policy the quadrupedal machine achieves locomotion skills that go beyond what had been achieved with prior methods.

These tremendous advances have fueled the confidence of researchers for solving more complex tasks that combine vision with language and action. VLN is a milestone instance of this trend. The capability of performing VLN well further enables a variety of higher level AI tasks, such as ALFRED task [9] where the agent is required to learn a mapping from natural language instructions and egocentric vision to sequences of actions for household tasks. Meanwhile, we can see that the VLN tasks are valuable for not only indoor environment [10] but outdoor environment from the aforementioned example.

In this survey, we will comprehensively review existing visual-and-language tasks, and discover that most of the approaches basically designed to solve only one task. In this case, we try to find out the internal difference among the VLN tasks. We can see that the difference of visual part is relative small. As no matter 2D or 3D, indoors or outdoors, and virtual or photo-realistic, all of them are environment perception alone the navigation trajectory. For example, tasks REVERIE [11] and Room-to-Room [1] are based on the same environment simulator. However, the language part leads these tasks completely different.

With this insight, we introduced a new taxonomy to catalog VLN tasks. According to how the language instructions are given, the VLN tasks can be divided into two types: single-turn and multi-turn.
For **single-turn** task, a serial of instructions is given before the agent starts to roll. Whether a route is specified, instructions can be divided into: *Goal-orientation* and *Route-orientation*.

- **Goal-orientation.** The instruction contains several goals, but no clue for how to get to them. The goals may be visible when a agent is at the start point. An agent can firstly find the goals, then plans the whole trajectory then finishes it. As all objects can been seen, researchers try to solve the low-level control challenges. However, the goals are invisible in some tasks. An agent have to search the objects in the environment.

- **Route-orientation.** An agent may get lost if it does not strictly follow the route containing in the instruction. The instruction may be well-formed. They can be decomposed into several meaningful pieces by some rules, each of them indicates an action. In this case, the agent can plan an action sequence then carries out it. All of the frontier researches, such as [12, 13], were under this framework. Even recently, the route instruction of the tasks in [14, 15, 16, 17, 18] are relatively simple to parse. Actually, a natural language instructions are unstructured and hard to parse. However, because of the surge development of deep learning, more and more interest are driven to tackle the unstructured instruction with deep neural networks. The most impressive task no doubt is Room-to-Room [1]. More details about the tasks of unstructured route-orientation instructions will be illustrated in the following sections.

For **multi-turn** tasks, the instructions will be given by a guide to a navigator in several turns. According to whether the navigator can response to the guide, tasks are divided into: *Imperative* and *Interactive*. As instructions can be given for several times, an instruction of one turn is mainly visible goal-orientation for easy execution.

- **Imperative.** The navigator can not respond to the guide, only execute the instructions.

- **Interactive.** Both the guide and the navigator can ask questions and share information, this is much more common in daily life.

To this end, we have briefly analyzed the instructions of VLN tasks. However, to train a VLN agent requires a ‘software stack’ [19]: (1) datasets providing 2D/3D assets with semantic annotations, (2) simulators that render these assets and within which an agent may be simulated, and (3) tasks that define evaluable problems that enable us to benchmark scientific progress. As shown in Tab. I, we summarize typical tasks and related simulators, the datasets will be illustrated in the following section. Beyond navigation, some tasks may interleave with other actions, such as manipulate an object, answer an question, locate a target object. Our taxonomy only considers the navigation part.

**Contributions.** First, we give a comprehensive review of the existing visual-and-language tasks. Compared to recent works, this survey covers more recent papers, more tasks and datasets. Second, the taxonomy of VLN tasks is well-designed, as shown in Fig. 1. Third, summaries and analyses are provided for each task from Section IV to Section VI. Limitations that are common to current approaches are also described and possible solutions given in Section VII. This may provide inspiring ideas for researchers in this field.

II. **Preliminaries**

In this section, we briefly provide technical background needed of VLN tasks. We review the effect of deep learning to Computer Vision, Natural Language Processing, Robotic navigation and Visual-Linguistic Learning, which are preliminaries of VLN tasks.
### Table I

**Taxonomies and Statics of VLN Tasks.** Beyond navigation, a task may interleave with other actions, the M, Q, L in column **Compound** mean that an agent is required to manipulate an object, answering a question, locate a target object, respectively. The Matterport3D in column **Simulator** means Matterport3D simulator. The - in column **Simulator** indicates the name of simulator is the same as the task, or not named.

| Task Type   | Instruction | Name       | Simulator     | Outdoor | Compound |
|-------------|-------------|------------|---------------|---------|----------|
| Single      |             | LANI [20]  | -             | -       | -        |
|             |             | ALFRED [9] | AI2-THOR [21]| M       |          |
|             |             | Talk2Car [22] | -             | ✓       | M        |
|             |             | XWORLD [23] | -             | -       |          |
|             |             | 3D Doom [34] | VizDoom [25] | -       | -        |
|             |             | Visual Semantic Navigation | AI2-THOR [21] | -       | -        |
| Single      |             | EQA [26]   | House3D [27] | Q       |          |
|             |             | RoomNav [27] | House3D [27] | -       |          |
|             |             | REVERIE [11] | Matterport3D [1] | L |          |
|             |             | Behavioral Robot Navigation [28] | - | - |          |
|             |             | Navigation Task Based on SUNCG [29] | - | - |          |
| Route-Orientation |             | Room-to-Room [1] | Matterport3D | -       |          |
|             |             | Room-for-Room [30] | Matterport3D | -       |          |
|             |             | Room-Cross-Room [31] | Matterport3D | -       |          |
|             |             | R6R, R8R [32] | Matterport3D | -       |          |
|             |             | Room-to-Room-CE [33] | Matterport3D | -       |          |
|             |             | Cross lingual Room-to-Room [34] | Matterport3D | -       |          |
|             |             | TouchDown [35] | Google Street View | ✓ | L        |
|             |             | RUN [36]   | -             | -       |          |
|             |             | Street Nav [37] | Google Street View | ✓ | -        |
|             |             | StreetLearn [38] | Google Street View | ✓ | -        |
|             |             | AARRAMON [39] | - | - | M        |
| Multi       |             | CEREALBAR [40] | - | - | -        |
|             |             | VLNA [41]  | Matterport3D | -       |          |
|             |             | HANNA [42] | Matterport3D | -       |          |
| Interactive |             | CVDN [43]  | Matterport3D | -       |          |
|             |             | Just Ask [44] | Matterport3D | -       |          |
|             |             | Talk The Walk [45] | - | ✓ | -        |
|             |             | RobotSlang [46] | Physical | - | -        |

https://developers.google.com/maps/documentation/streetview/intro

### A. Computer Vision

The advent of deep learning [47] has tremendously changed the field of computer vision. The best way to represent images is by leveraging automatic feature extraction methods. Convolutional Neural Networks (CNNs) [48] have become the de facto standard for generating representations of images using end-to-end trainable models. Residual Networks He et al. [2] make the layer number of the network increase from a dozen to dozens, or even more than 100.

With these novel architecture, all task of computer vision, such as Image Classification, Object Localization, Object Detection, Object Segmentation, Object Identification, Instance segmentation and Panoptic segmentation, have made tremendous progress.

### B. Statistical Natural Language Processing

Language is usually represented either with bag-of-words or with sentence representations. Modern approaches use word vectors to capture or learn structure, such as Long Short-Term Memory units (LSTMs) [49] combined with Word2Vec [50] or Paragraph Vector [51]. These approaches learn a vector representation associated with either words or longer documents and then compute over an entire sentence to perform tasks such as shallow parsing, syntax parsing, semantic role labeling, named entity recognition, entity linking, co-reference resolution, etc.

### C. Robot Navigation

Navigation is an important ability for artificial agents to adapt to an environment and is the precondition for other advanced behaviors. Robot navigation task expects robot find optimal path to reach the destination, typical navigation tasks including standard vision-based navigation using only visual input [52, 53] and natural language instruction based navigation [12, 54]. Furthermore, combining vision and language information during navigation task is more challenging and realistic, because natural language navigation instruction should be interpreted based on visual input, just like humans.

### D. Visual-Linguistic Learning

The deep learning advances the development of both computer vision and natural language processing. Moreover, it unifies the visual and language data into a vector representation. This is the most important preliminary to combine vision with language and high-level reasoning. Visual Question Answering [55, 56, 57, 58] is a prime example of this trend. Others are image captioning [59, 60, 61], visual commonsense reasoning [62, 63] and so on.

### III. Datasets and Simulators

Considering of the scale, annotation and influence, we will introduce some typical datasets ans simulators. Other datasets...
or simulators will be briefly referred alone the introduction of related tasks.

A. Datasets

**SUNCG** [64] dataset contains 45,622 artificially designed 3D scenes, ranging from single chamber to multi-floor houses. These 3D scenes include a large number of objects, spatial layout and other elements, hoping to provide a good platform for 3D object recognition researchers. On average, there are 8.9 rooms and 1.3 floors per scene. There is a diverse set of room and object types in each scene. More than 20 types of room and 80 categories of object in SUNCG datasets, 404,508 room instances and 5,697,217 object instances.

People have annotated each scene in dataset with 3D coordinates and inside room and object types. At every time step an agent has access to the following signals: a) the visual RGB signal of its current first person view, b) semantic/instance segmentation masks for all the objects visible in its current view, and c) depth information. For different tasks, these signals might serve for different purposes, e.g., as a feature plane or an auxiliary target.

**Matterport 3D** [65] is a recent mainstream dataset, which contains 90 scenes collected from reality and 194,400 RGB-D images in total. Dataset have been fully annotated with 3D reconstructions and 2D and 3D semantic segmentation.

The precise global alignment of the entire building and a comprehensive and diverse panoramic view set supports various supervised and self-supervised computer vision tasks, such as view overlap prediction, semantic segmentation, and region classification etc.

**2D-3D-S** [66] is an indoor environment supporting 2D, 2.5D and 3D domains with multi-modal, and 3D meshes and point clouds.

The dataset has over 70,000 RGB images, annotated with fully information such as depths, semantic annotations, and camera configuration.

**Replica** [67] is a photo-realistic 3D indoor environment with 18 different scenes rendered by high quality image. The scenes selected focus on the semantic diversity and scale of the environment. Each scene is composed of dense grids, high-resolution textures, original semantic class and instance information, and flat mirrors and glass reflectors.

B. Simulators with Builtin Dataset

**LANI** [20] is a massive 3D navigation dataset with 6,000 language instructions in total, based on Unity 3D. The environment is a fenced, square, grass field. Each scene includes between 6–13 randomly placed landmarks, sampled from 63 unique landmarks. The agent has discrete actions: forward, stop, turnleft, and turnright. At each time step, the agent performs an action, observes a first person view of the surroundings as an image, and receives a scalar reward. The simulator provides a socket API to control the agent and the environment.

**AI2-THOR** [21] is a large-scale photo-realistic 3D indoor dataset, where agents can navigate in the scenes and interact with objects to perform tasks. AI2-THOR enables research in many different domains, such as deep reinforcement learning, planning, visual question answering, and object detection and segmentation etc.

**VizDoom** [25] is modified on a first-person shooter video game, Doom. Aiming at providing convenience for researchers, VizDoom is designed small-scale, efficient, and highly customizable for different domains of experiments. The main functions include different control modes, custom scenes, access to the depth buffer and off-screen rendering, without the need for a graphical interface.

**Gibson** [68] is based on virtualizing real spaces, with embodiment of agents and making them subject to constraints of complex semantic scene. Gibson consists of 572 building scenes and 1,447 floors, and each scene are equipped with panoramas image and camera configurations. The base format of the dataset is similar to 2D-3D-Semantics dataset [66], but is more diverse and includes 2 orders of magnitude more spaces. The simulator of Gibson has also integrated 2D-3D-Semantics dataset [66] and Matterport3D [65] for optional use.

C. Simulators

**House3D** [27] is having a diverse room types and objects inside. The 3D scenes are based on SUNCG dataset and annotated with rich information. To build a realistic 3D environment, House3D offers a OpenGL based renderer for the SUNCG scenes. Agent in this environment can move freely, receiving tasks for the different kinds of research.

**Matterport3D Simulator** [1] is a large-scale visual reinforcement learning simulation research platform based on the Matterport3D dataset [65]. Agent can move in the entire scene by adopting a pose consistent with the panoramic viewpoint. Each scene is equipped with a weighted, undirected graph, so that the presence of an edge indicates the navigable transition of the robot between the two view points. And move from one viewpoint to another along any edge in the navigation graph. The simulator does not define or place restrictions on the agent’s goal, reward function, or any additional context.

**Habitat** [19] is a platform for research in photo-realistic 3D environment. Specifically, Habitat consists of a simulator Habitat-Sim and a modular library Habitat-API. The simulator supports Matterport3D [65], Gibson [68], and Replica [67] datasets. Habitat-API aiming to help researchers verify and improve intelligent algorithms.

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IV. GOAL-ORIENTATION TASKS

A. LANI

1) Task Definition: Misra et al. [20] collected a corpus of navigation instructions using crowd sourcing. They used LANI simulator to generate environments randomly, and generate one reference path for each environment. The generated reference paths were near to their neighbor landmarks to elicit instructions. Then, they used Amazon Mechanical Turk to annotate.

The whole environment is simulated and relatively simple. Furthermore, Blukis et al. [69] proposed a real-world learning framework, which is similar to LANI.

2) Evaluation Metric: The task performance is evaluated on a test set \( \{ (\hat{x}^{(i)}, s_1^{(i)}, s_0^{(i)}) \}_{i=1}^M \), where \( \hat{x}^{(i)} \) is an instruction, \( s_1^{(i)} \) is a start state, and \( s_0^{(i)} \) is the goal state. Task completion accuracy and the distance of the agent’s final state to \( s_0^{(i)} \) are evaluated.

3) Related Task: Before LANI, Blukis et al. [70] proposed a virtual environments navigation task based on Unreal Engine\(^{11}\), which uses the AirSim plugin [71] to simulate realistic quadcopter dynamics. The agent is a quad-copter flying between landmarks. This work focus on the problem of mapping, planning and task execution. And language instructions generated from a pre-defined set of templates.

In Blukis et al. [70], a baseline approach was proposed. It puts instruction into an LSTM network to get language embedding at the task beginning. A custom residual network is used to represent the image feature at every time step, and then project the feature in global reference frame.

4) Typical Methods: In [20], the instruction execution was decomposed into goal prediction, action generation. They proposed a new language-conditioned image generation network architecture LINGUNET, to make a map from visual input to goals output.

Base on LANI, Blukis et al. [72] proposed an approach for mapping natural language instructions and raw observations inputs to continuous control of a quadcopter drone, which used the quadcopter simulator environment from Blukis et al. [70]. For indicating where the agent should visit during navigation and where to stop, they built a model to predicts the position-visitation distributions. then, actions are generated from the predicted distributions.

For combing the simulation and reality, Blukis et al. [69] proposed a learning framework to map language and image to low-level action output. In addition, Supervised Reinforcement Asynchronous Learning (SuReAL) is used in both simulation and reality without the need to fly in real world during training. SuReAL combines supervised learning for predicting next goal and reinforcement learning for continuous action output.

More recently, Blukis et al. [73] studied the problem of extending to reason about new objects. Due to the lack of sufficient training data, they used a few-shot method trained from extra augmented reality data to ground language to object. This method can align the objects and their mentions in language instruction.

B. Action Learning From Realistic Environments and Directives

1) Task Definition: Action Learning From Realistic Environments and Directives [9](ALFRED) is a indoor task, agent in this task need to receive a language instruction about doing a household and first-person image observation, then generated a sequence of actions to finish it. ALFRED includes 25,743 English instructions, describing 8,055 expert demonstrations, each with an average of 50 steps, resulting in 428,322 image-action pairs. The expert demonstrations are together with both high-level and low-level language instructions in 120 indoor scenes based on AI2-THOR 2.0 simulator [21]. These demonstrations involve partial observability, a long range of actions, in a designated natural language, and irreversible actions.

2) Evaluation Metrics: ALFRED allows users to evaluate both full task and task goal-condition completion. In navigation-only tasks, one can only measure how far the agent is from the goal. Whether the target conditions of the task have been completed can also be evaluated in the ALFRED task. The evaluation metrics consist of Task Success, Goal-Condition Success and Path Weighted Metrics.

Task Success. If the object positions and state changes correspond correctly to the task goal-conditions at the end of the action sequence, the task success will be set to 1, and otherwise to 0.

Goal-Condition Success. The goal-condition success is the ratio of goal-conditions completed at the end of an episode to those necessary to have finished a task.

Path Weighted Metrics. Anderson et al. [74] found that PDDL solver can not find the optimal result, but usually efficient. The path weighted score \( p_s \) for metric \( s \) is given as

\[
p_s = s \times \frac{L^*}{\max(L^*, \bar{L})}
\]  

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\(^{11}\)https://www.unrealengine.com
where $\hat{L}$ is the number of actions the model took in the episode, and $L^*$ is the number of actions in the expert demonstration. Obviously, a model receives half-credit for taking twice as long as the expert to accomplish a task.

3) Typical Methods: In [9], a Sequence-to-Sequence Model with progress monitoring was introduced. Each visual observation was encoded with a froze ResNet-18 [2]. The step-by-step instructions was combined into a single input sequence with the $<\text{SEP}>$ token. This word sequence was fed into a bi-directional LSTM encoder to produce an encoding sequence. The agent’s actions at each time step are based on an attention mechanism that can identify the related tokens in the language instruction. The agent interacts with the environment by choosing an action and producing dense pixel-wise binary mask to indicate specific objects in the frame.

In [75], during the navigation of the sub-goals, the agent’s field of view is enhanced through multiple perspectives, and the agent is trained to predict its relative spatial relationship with the target position at each time step.

Singh et al. [76] proposed a Modular Object-Centric Approach (MOCA) to decouple ALFRED task into two sub-task, i.e., visual perception and action policy generation. The former aiming to predicts an interaction mask for the object that the agent interacts with using object-centric mask prediction, while the latter makes a prediction of the current action of the agent.

C. Embodied Question Answering

1) Task Overview: Das et al. [26] build EQA on a pruned subset of environments from House3D [27], more details about House3D please refer to section III.

In order to ensure the quality of the dataset, the environment inside must be realistic and typical, and there must be no abnormal conditions. Moreover, the minimum configuration requirements for each environment are also put forward, i.e., at least one kitchen, dining room, living room, and bedroom.

The EQA v1 dataset contains more than 5000 questions in over 750 environments, involving a total of 45 unique objects in 7 unique room types. There are 1 to 22 related questions in each environment, with an average of 6. Preposition questions are less than other kinds of questions because many frequently occurring spatial relationships are too easy to solve without exploration and cannot be processed by entropy threshold.

In EmbodiedQA, the agent does not receive any global or structured representation of the environment (map, location, rooms, objects), or of the task (the functional program that generated the question).

2) Evaluation Metrics: The goal of an EQA agent is to answer questions precisely. However, it is important to disentangle success/failure at the intermediate task of navigation from the downstream task of question answering. The evaluation metrics of this task are as following:

Question Answering Accuracy. A probability distribution of all candidates answer are generated by the model and rank the answer from high probability to low. Then compute over test questions from EQA and get the mean rank of the ground-truth.

Navigation Accuracy. The navigation performance is evaluated by reporting the distance to the target object at navigation termination ($d_T$), change in distance to target from initial to final position ($d_\Delta$), and the smallest distance to the target at any point in the episode ($d_{\text{min}}$). All distances are measured in meters along the shortest path to the target. Other additional metrics are:

- the percentage of questions for which an agent either terminates in ($\%r_T$)
- ever enters ($\%r_{\text{ever}}$) the room containing the target object(s)
- the percentage of episodes in which agents choose to stop navigation and give a answer before reaching the maximum episode length ($\%r_{\text{stop}}$)

3) Typical Methods: In [26] give a baseline model, model has four sub-modules: vision, language, navigation, answering, and is trained from raw sensory input (pixels and words) to goal-driven multi-room indoor navigation to visual question answering. The training process is divided into two stages. At beginning, the navigation and answer module uses imitation/supervised learning to independently train the automatically generated navigation expert demonstrations. Then, the navigation architecture uses policy gradients for fine-tuning.

Anand et al. [77] explored blindfold (question-only) baselines for EQA which neglect environmental and visual information. Intuitively, the blindfold method is a degraded solution, but it reaches state-of-the-art results on EQA except some rare initialization situations.

Das et al. [78] proposed a modular approach for learning strategies for navigating within long-term planning from instructions. For increasing sample efficiency, imitation learning is used to warm-start policies at each level of the hierarchical policy on multiple timescales.

Parvaneh et al. [79] proposed a new learning strategy that learns both from observations and generated counterfactual environments.

An algorithm generating counterfactual observations on the fly for navigation is introduced as the linear combinations of present environments. In addition, the agent’s actions is encouraged to remain stable between initial and counterfactual environments by training objective–effectively removing false features that would bias the agent.

Furthermore, Wu et al. [80] introduced an easier and practical and EQA setting called calibration. They designed a warm-up stage that the agent was asked a few rhetorical questions when it entered into a new environment. The goal was to adapt the agent policy to the new environments. And they proposed a new model, which contained two modules, designed for the intermediate navigation task, called Navigation Module, and downstream question answering task, called Question Answering Module, respectively.

4) Task Variation: Wijmans et al. [81] extended the EQA task in realistic environments from the Matterport3D dataset [65]. When using behavioral cloning to train a recurrent model for navigation, the impact of a novel loss-weighting metric named Inflection Weighting has grown. The model can
surpass the baseline by optimize the infection weighting metric. Moreover, they argue that point clouds can provide more information than traditional RGB image in photo-realistic environment, especially for task like embodied navigation and obstacle avoidance.

Yu et al. [82] extends the EQA to Multi-Target version, i.e., Multi-Target EQA. Because the question is more complex, the agent must navigate to multiple locations and perform some comparative reasoning steps before answering the question. A new model was designed to solve MT-EQA. It consists of 4 modules: the question-to-program generator, the navigator, the controller, and the VQA module.

D. RoomNav

1) Task Overview: Wu et al. [27] proposed an environment House3D, then developed the Concept-Driven Navigation, called RoomNav. The goal is defined as "Go to X", where X represents a pre-defined room type or object type. This is a semantic concept, and the agent needs to be interpreted from a variety of scenes with different visual appearances. RoomNav consists of 270 houses divided into three splits, i.e., small, large and test with 20, 200, and 50 respectively.

Observation: Three different kinds of visual input signals were utilized for $X_t$, including (1) raw pixel values; (2) semantic segmentation mask of the pixel input; and (3) depth information, and experiment with different combinations of them. Each concept $I$ was encoded as a one-hot vector representation.

Action Space: Similar to existing navigation works, the task defined a fixed set of actions, here 12 in number including different scales of rotations and movements. Due to the complexity of the indoor scenes, the task also explored a continuous action space similar to Lowe et al. [83], which in effect allows the agent to move with different velocities. In all cases, if the agent hits an obstacle it remains still.

2) Evaluation Metrics: An episode is considered successful if both of the following two criteria are satisfied: (1) the agent is located inside the target room; (2) the agent consecutively sees a designated object category associated with that target room type for at least 2 time steps. An agent sees an object if there are at least 4% of pixels in $X_t$ belonging to that object.

3) Typical Methods: In [27], a gated-attention architecture is introduced. Gated-CNN and gated-LSTM network are used for controlling continuous and discrete actions respectively. The gated-CNN policy is trained using the Deep Deterministic Policy Gradient (DDPG) [84], while the gated-LSTM policy is trained using the asynchronous advantage actor-critic algorithm (A3C) [85].

Wu et al. [86] introduced a new memory architecture, Bayesian Relational Memory (BRM), taking the form of a probability relationship graph on semantic entities to improve the generalization ability in unseen environments. BRM supports obtaining some prior knowledge from the training environment, and at the same time, it can update the knowledge in memory after exploration. A BRM agent consists of a module for generating sub-goals and goal-conditioned locomotion module for control.

E. Remote Embodied Visual referring Expression in Real Indoor Environments

1) Task Overview: Remote Embodied Visual referring Expression in Real Indoor Environments - REVERIE [11] task requires the intelligent agent to correctly locate the remote target object specified by the concise high-level natural language instructions (which cannot be observed at the starting position). Since the target object and the starting object are in different rooms, the agent needs to navigate to the target location first.

Formally, at the beginning of each episode, the agent is given as input a high-level natural language instruction $X = \langle w_1, w_2, \cdots, w_L \rangle$, where $L$ is the length of the instruction and $w_i$ is a single word token. Following the common practice in VLN, the agent has access to surrounding panoramic images $V_0 = v_{0,k}, k \in 1,\ldots,36$ and navigable viewpoints at the current location, where $v_{0,k}$ is determined by the agent’s states comprising a tuple of 3D position, heading and elevation $\theta_{0,k} \equiv \langle p_0, \psi_{0,k}, \theta_{0,k} \rangle$ (3 elevation and 12 heading angles are used). Then the agent needs to make a sequence of actions $< a_0, \cdots, a_T >$ to reach the goal location, where each action is choosing one of the navigable viewpoints or choosing the current viewpoint which means to stop. The action can also be a ‘detecting’ action that outputs the target object bounding-box refereed by the instruction. If the agent ‘thinks’ it has localised the target object and decides to output it, it is required to output a bounding box or choose from several candidates provided by the simulator. A bounding box is denoted as $b_x, b_y, b_w, b_h$, where $b_x$ and $b_y$ are the coordinate of the left-top point, $b_w$ and $b_h$ denote the width and height of the bounding box, respectively. When agent generates a bounding box of target, this episode is finished.

2) Evaluation Metrics: The performance of a model is mainly measured by REVERIE success rate, which is the number of successful tasks over the total number of tasks. A task is considered successful if it selects the correct bounding box of the target object from a set of candidates. Because the target object can be observed at different viewpoints or camera views, we treat it as a success as long as the agent can identify the target within 3 meters, regardless of from different viewpoints or views. We also measure the navigation performance with four kinds of metrics, including success rate, oracle success rate, success rate weighted by path length, and path length (in meters) [1]. In the task, a navigation is considered successful only when the agent stops at a location within 3 meters from the target object.

3) Typical Methods: In [11], the authors proposed a module including three parts: a navigator module that decides the action to take for the next step, a pointer module that attempts to localise the target object according to the language guidance, and an interaction module that responds for sending the referring expression comprehension information obtained from the pointer to the navigator to guild it to make more accurate action prediction.

Lin et al. [87] introduce two pre-training tasks, called Scene Grounding task and Object Grounding task, and a new Memory-augmented attentive action decoder. The pre-training tasks encourage agent learn where to stop and what to attend...
to, and the action decoder uses past observations to merge visual and textual information in an effective way.

F. Other Tasks

1) Talk2Car: Talk to car task is proposed by Deruyttere et al. [22], and the dataset for this task is built upon the nuScenes dataset [88]. This dataset includes 11,959 instructions for the 850 videos of nuScenes training set since 3D bounding box annotations for the test set of nuScenes are not available. 55.94% and 44.06% of these commands belong to videos taken respectively in Boston and Singapore. On average a command consist of 11.01 words, 2.32 nouns, 2.29 verbs and 0.62 adjectives. Each video has on average 14.07 commands. The textual annotations are very complete, it not only indicates what to do, such as ‘pick him up’, but how to drive the car, such as ‘turn around’.

However, this task did not give a metric to evaluate the performance of the action.

In [22], the authors only worked with detecting the referred object, ignored the action execution. They only assessed the performance of 7 detection models to find the objects in a command. In the test set, random noun matching approach was used to match the nouns in command with the visual objects.

2) XWORLD: This task is proposed by Yu et al. [89]. It consists of XWORLD2D and XWORLD3D.

XWORLD2D. To test the method of interactive grounded language acquisition and generalization. Yu et al. [23] built a 2D maze-like world, i.e., XWORLD2D. And navigation and question answering sub-task are language related. Navigation task requires agent to follow the language instructions to navigate the final destination, and question answer task requires agent generate one-word answers to questions.

XWORLD3D. The XWORLD3D is a extension of XWORLD2D where changing the environment from full-observability to partial-observability. And two actions turn_left and turn_right added to the action set, of which the yaw changes are both 90°. To increase the visual variance, at each session the authors randomly rotate each object and scale it randomly within [0.5, 1.0]. Suppose each map is $X \times Y$, then a session will end after $3XY$ time steps if a success or failure is not achieved.

In addition, environment layout and the agent’s action in XWORLD3D are discrete. Success means the agent acts obey the teacher’s command. A failure is triggered whenever the agent hits any object that is not required by the command. The success rate is used to evaluation the performance.

In [23], an effective baseline method Guided Feature Transformation (GFT) is proposed for language grounding. In order to improve the fusion of visual and language feature, the latent sentence embeddings calculated from the language input is regarded as the conversion matrix of visual features. This method is completely differentiable and is embedded in the navigation agent’s perception system, which is trained end-to-end by the RL. The agent trained by GFT can adapt to both 2D and 3D environments without changing any architecture or hyperparameters between the two scenarios.

3) 3D Doom: Chaplot et al. [24] created an environment for language grounding research, where the agent need to follow natural language instruction and receive positive rewards on after successfully completing the task. This environment is built on top of the VizDoom API [25], based on Doom, a classic first person shooting game.

In 3D Doom task, an instruction is (action, attribute(s), object) triplet. Each instruction can have multiple attributes, but the number of actions and objects is limited to one each. This environment allows various objects to be generated at different locations on the map. Objects can have various visual attributes. Success rate defined as the proportion of success navigation times in the total number of times. There are two scenarios for evaluation:

Multi-task Generalization. The agent uses the instructions in the training set for evaluation on an unseen map. The unseen map consists of a combination of invisible objects placed at random locations. In this scenario, the test agent will not overfit or memorize the training map, and can execute multiple instructions or tasks on an unseen map.

Zero-shot Task Generalization, where the agent is situated in unseen environment with new combinations of attribute-object pairs which are not seen during the training. The maps in this scenario are also unseen.

The model proposed by [24] uses the Gated-Attention mechanism to combine image and text representations, and uses standard reinforcement and imitation learning methods to learn strategies for executing natural language instructions. This model is consisted of a State Processing Module and a Policy Learning Module, and trained end-to-end.

4) Visual Semantic Navigation: This task [90] is based on the interactive environments of AI2-THOR [21]. There are 87 object categories within AI2-THOR that are common among the scenes. However, some of the objects are not visible without interaction. Therefore, only $|V| = 53$ categories based on their visibility at random initialization of the scenes. To test the generalization ability of the method on novel objects, the 53 object categories are split into known and novel sets. Only the known set of object categories are used in training. Only the navigation commands of AI2-THOR were used for the task. These actions include: move forward, move back, rotate right, rotate left, and stop.

The evaluation metrics are Success Rate and the Success weighted by Path Length (SPL) metric recently proposed by Anderson et al. [74].

- Success Rate is defined as the ratio of the number of times the agent successfully navigates to the target and the total number of episodes.
- SPL is a better metric which is a function considering both Success Rate and the path length to reach the goal from the starting point. It is defined as $\frac{1}{N} \sum_{i=1}^{N} S_i \max(P_i, L_i)$, where $N$ is the number of episodes, $S_i$ is a binary indicator of success in episode $i$, $P_i$ represents path length and $L_i$ is the shortest path distance (provided by the environment for evaluation) in episode $i$.

Based on the actor-critic model [85], Yang et al. [90] proposed to use Graph Convolutional Networks (GCNs) [91]
to incorporate the prior knowledge into a Deep Reinforcement Learning framework.

5) Behavioral Robot Navigation: Zang et al. [28] created a new dataset for the problem of following navigation instructions under the behavioral navigation framework of [92]. This dataset contains 100 maps of simulated indoor environments, each with 6 to 65 rooms. It consists of 8066 pairs of free-form natural language instructions and navigation plans for training. This training data was collected from 88 unique simulated environments, totaling 6064 distinct navigation plans (2002 plans have two different navigation instructions each; the rest has one). The dataset contains two test set variants:

Test-Repeated: uses seen trainset environments and unseen routes, including 1012 pairs of instructions and navigation plans.

Test-New: uses 12 unseen environments and unseen routes, which is more complex, including 962 pairs of instructions and navigation plans.

An end-to-end deep learning model is proposed by Zang et al. [28] to convert free-form natural language instructions into high-level navigation plans.

6) Navigation Task Based on SUNCG: Fu et al. [29] introduced a navigation task based on SUNCG [64]. In this task, the agent is given a location which corresponds to a room or object, and the agent must navigate through the house to reach the target location. The language commands were generated based on a preset grammar, and using names of objects and locations associated with the task. The form is "go to X", where X stands for names of locations and objects within the environment.

Furthermore, Fu et al. [29] proposed Language-Conditioned Reward Learning (LC-RL), which grounds free-form natural language commands as reward functions using inverse reinforcement learning.

V. ROUTE-ORIENTATION TASKS

A. Room-to-Room

1) Task Description: Room-to-Room (R2R) is a natural language navigation dataset based on vision in a photo-realistic environment [1].

Environments in this dataset is defined by a navigation graph, where nodes are locations with a self-centered egocentric panoramic image, and edges define effective connections for agent navigation. This dataset(spited with train/validation/test) is fully annotated with instructions and paths and each path has 3 different related instructions. The average length of ground-truth path is 4 to 6 edges.

R2R is a task where the inputs are the images from egocentric panoramic camera and instruction. Note that images are updating with the motion of agent, while instruction is given at the beginning. For example, given an instruction "Go towards the front door but before the front door make a left, then through the archway, go to the middle of the middle room and stop", our agent should understand the instruction and follow it from start point to the goal position as soon as possible.

2) Evaluation Metrics: There are a bunch of metrics to evaluate a VLN agent. Typical used are the Success Rate, Navigation Error, Path Length and the Success weighted by Path Length. The Oracle Navigation Error, Oracle Success Rate can be used to monitor the training process.

- Success Rate (SR) shows how many times the last node of the predicted path is within a certain threshold distance of the last reference path node.
- Navigation Error (NE) measures the distance between the last predicted path node and the last reference path node.
- Path Length (PL) is equal to the total length of the predicted path. It is of course optimal when it’s equal to the length of the reference path.
- Success weighted by Path Length (SPL) [1] takes into account both Success Rate and path length. What it does not consider is the similarity between the intermediate nodes of the predicted path and the reference path. This poses the problem that even though it displays a high score that predicted path did not really follow the spoken instructions but only got the goal right.
- Oracle Navigation Error (ONE) measures the smallest distance from any node in the path to the reference goal node.
- Oracle Success Rate (OSR) measures how often any node in the path is within a certain threshold distance from the goal. The goal is represented by the last node of the reference path.

Using automatically generated navigation instructions as additional training data can enhance the model performance. However, the quality of instructions generated by existing instruction generators lacks a comprehensive evaluation, so many researchers have made contributions in evaluating instructions.

Huang et al. [93] proposed a discriminator model that can predict how well a given instruction explains the paired path, showing that only a small portion of the augmented data in [94] are high fidelity. This metric can evaluate the instruction-path pair, which improves training efficiency and reduces the training time cost. Ilharco et al. [95] introduced the normalized Dynamic Time Warping (nDTW) metric.

nDTW slightly penalizes deviations from the ground-truth path and it is naturally sensitive to the order of the nodes composing each path. Another advantage of nDTW is suited for both continuous and graph-based evaluations, and can be efficiently calculated. Despite the performance of R2R task has improved rapidly, current research is not clear about the role language understanding in this task, since mainstream evaluation metrics are focused on the completion of the goal, rather than the sequence of actions corresponding to the language instructions. Here, Jain et al. [30] analyzed the drawbacks of current metrics for the R2R dataset and designed a novel metric named Coverage weighted by Length Score (CLS). CLS measures how closely an agent’s trajectory fits with ground-truth path, not just the completion of the goal. To improve instruction evaluation, Zhao et al. [96] proposed an instruction-trajectory compatibility model that operates without reference instructions. In the case of grounded navigation instructions,
for model selection in the presence of reference instructions they recommend using the SPICE metric. In all other scenarios (e.g., selecting individual instructions, or model selection without reference instructions) they recommend using a learned instruction-trajectory compatibility model.

3) Typical Methods: The R2R task is most impressive, and most research works of VLN are based on it. Basic framework of these works are Sequence-to-Sequence (Seq-2-Seq), but they focus on different aspects to improve performance, therefor we divide them to 7 classes for clear understanding.

Exploration Strategy. In this class, related works focus on finding a effective and fast path from start to goal point. Ma et al. [97] proposed a module to estimate the progress that made by agent towards the goal. Based on that, Ma et al. [98] designed two module for exploration, i.e., Regret Module for moving forward or rolling back and Progress Marker to help the agent decide which direction to go next by showing directions that are visited and their associated progress estimate. While all current approaches make local action decisions or score entire trajectories using beam search, Ke et al. [99] presented the Frontier Aware Search with backTracking (FAST) navigator. When an agent finds lost itself, FAST navigator can explicit backtrack by using asynchronous search. This can also be plug and play on other models. Huang et al. [100] defined two in-domain accessorial sub tasks: cross-modal alignment (CMA) and next visual scene (NVS). The visual and textual representations of agent learned in certain environment can be transferred to other environments with the help of CMA and NVS. Zhu et al. [101] introduced four self-supervised auxiliary reasoning tasks to take advantage of the additional training signals derived from the semantic information. These auxiliary task improve the model performance by giving more semantic information to help agent understanding the environment and task. Wang et al. [102] introduced an end-to-end architecture for learning an exploration policy in some important decision-making problem such as exploration occasion and direction, and following exploration strategy.

In [103], a learning scheme using recursive alternate imitation and exploration is proposed to narrow the difference between training and inference. Then further exploited the advantages of both these two learning schemes via adversarial learning. Deng et al. [104] introduced the Evolving Graphical Planner (EGP), a method that uses raw image to generate global planning efficiently. It’s strength lies in constructs a graphical representation dynamically and generalizing the action space to allow for more flexible decision making.

Beyond Seq-2-Seq Architecture. Encouraged by recent work on fully-attentive networks, many transformer-based researches are conducted. It is an extension of Sequence to sequence architecture.

Landi et al. [105] devised Perceive, Transform, and Act (PTA) architecture to use the full history of previous actions for different modalities. Magassouba et al. [106] proposed the Cross-modal Masked Path (CrossMap) Transformer, which encodes linguistic and environment state features to sequentially generate actions similarly to recurrent network approaches. In addition, model uses feature masking to better model the relationship between the instruction and environment features. Wu et al. [107] and Mao et al. [108] used Multi-head attention on visual and textual input to enhance the performance of the model. To capture and utilize the inter-modal and intra-modal relationships among the scene, its objects, and directional clues, Hong et al. [109] devised Language and Visual Entity Relationship Graph model. A message-passing algorithm is also proposed to spread information between the language elements and visual entities in the graph, and then these agents are combined to determine the next action to be taken. Xia et al. [110] presented a novel training paradigm, Learn from Everyone(LEO), which utilize multiple language instructions (as multiple views) for the same path to resolve natural language ambiguity and improve generalization capabilities. Qi et al. [111] distinguished the object and action information from language instruction in which most existing method pay few attentions, and proposed a Object-and-Action Aware Model (OAAM) that processes these two different forms of natural language based instruction separately. OAAM enables each process to flexibly match object-centric/action-centric instructions with their corresponding visual perception/action direction. To capture environment layouts and make long-term planning, Wang et al. [112] presented Structured Scene Memory (SSM), that allows VLN agents to access to its past perception and explore environment layouts. With this expressive and persistent space representation, agent shows advantages in fine-grained instruction grounding, long-term reasoning, and global decision-making.

Reinforcement Learning and Imitation Learning. Many work have found it is beneficial to combine imitation learning and reinforcement learning. All of Wang et al. [113], Tan et al. [114], Hong et al. [109], Parvaneh et al. [115] and Wang et al. [102] trained their model with two distinct learning paradigms, i.e., 1) imitation learning, where agent is forced to mimic the behavior of its teacher. 2) reinforcement learning, can help the agent explore the state-action space outside the demonstration path. Specifically, in imitation learning, the agent takes the teacher action $a^*_t$ at each time step to efficiently learn to follow the ground-truth trajectory. In reinforcement learning, the agent samples an action $a^*_t$ from the action probability $p_t$ and learns from the rewards, which allows the agent to explore the environment and improve ability of generalization. Combining IL and RL balances exploitation and exploration when learning to navigate, formally, we have:

$$
L = \lambda \sum_{t=1}^{T} -a^*_t \log(p_t) + \sum_{t=1}^{T} -a^*_t \log(p_t)A_t
$$

For improving generalization ability, Wang et al. [116] integrated model-based and model-free reinforcement learning method which is a hybrid planned-ahead model, and outperforms than baselines. Later, Wang et al. [113] used Reinforced Cross-Modal Matching (RCM) method with extrinsic and intrinsic rewards. The novel cycle-reconstruction reward is introduced to match the instruction and trajectory globally. In [117], based on SEED RL architecture, Vision and Language Agent Navigation(VALAN) is introduced as a lightweight and extensible framework for learning algorithm.
research. In order to reduce the impact of reward engineering design and generalization, Soft Expert Reward Learning (SERL) model is proposed by Wang et al. [118], which contains two auxiliary module: Soft Expert Distillation and Self Perceiving. The former activate agent to explore like an expert while the latter enforces the agent will reach the goal as soon as possible. Zhou and Small [119] devised a adversarial inverse reinforcement learning method to learn a language-conditioned policy and reward function. For better adapt to the new environment, variational goal generator is used during training to relabel the trajectory and sample different targets.

**Language Grounding.** Wang et al. [113] presented a novel cross-modal grounding architecture to ground language on both local visual information and global visual trajectory. Hu et al. [120] proposed to decompose the grounding procedure into a set of expert models with access to different modalities (including object detection) and ensemble them at prediction time, in order to better use all the available modalities. In order to enable the agent to better track the correspondence between text and visual modalities, a cross-modal grounding module composed of two complementary attention mechanisms is designed by Zhang et al. [103]. Kurita and Cho [121] built a neural network to compute the probability distribution over all possible instructions, and used Bayes’ rule to build a language-grounded policy. This method has interpretability than the traditional discriminative method by conducting comprehensive experiments. Hong et al. [122] argued that the granularity of the navigation task should be at the level of these sub-instructions, rather than attempting to ground a specific part of the original long and complex instruction without any direct supervision or measure navigation progress at word level.

**Data Augmentation.** Fried et al. [94]propose a speaker-follower framework for data augmentation and reasoning in supervised learning. Hong et al. [122] enrich the benchmark dataset R2R with sub-instructions and their corresponding paths, i.e., Fine-Grained Room-to-Room (FGR2R). By pairing the sub-commands with the corresponding viewpoints in the path, FGR2R can better give the agent sufficient semantic information during the training process. Agarwal et al. [123] presented a work-in-progress “speaker” model that generates navigation instructions in two steps First, hard attention is used to select a series of discrete visual landmarks along the trajectory, and then a language conditioned on these landmarks is generated for the second time. Different from traditional data augmentation methods, Parvaneh et al. [115] proposed an efficient algorithm to generate counterfactual instances that do not depend on hand-made or the particular field of rules, they are instantly generated. These counterfactual instances are added to the training, improving the ability of the agent when testing extended to the new environment. In [124], counterfactual idea has another application. A model agnostic method called Adversarial Path Sampler (APS) is introduced to sample paths to optimize the agent navigation strategies gradually. Yu et al. [125] simultaneously dealt with the scarcity of data in the R2R task while removing biases in the dataset through random walk data augmentation. By doing so, they are able to reduce the generalization gap and outperform baselines in navigating unknown environments. An et al. [126] designed a module named Neighbor-View Enhanced Model (NvEM) to adaptively fuse the visual context from the neighbor views at the global level and the local level. Liu et al. [127] proposed Random Environmental Mixup (REM) aiming to reduce the performance gap between the seen and unseen environment and improve the overall performance. This method breaks up the environment and the corresponding path, and then recombines them according to certain rules to construct a brand-new environment as training data. Sun et al. [128] pointed that depth as a valuable signal source for the navigation has not yet fully explored and thus been ignored in previous research. Hence, they proposed a Depth-guided Adaptive Instance Normalization module and Shift Attention (DASA) module to address this issue.

**Pre-Training model.** The general feature representation obtained through pre-training can be applied to various tasks, and has been confirmed in many fields. A strong pre-trained backbone network can be effective in improving downstream task, like image recognition in CV and question answering in NLP. In particular, Transformer networks Vaswani et al. [129] pre-trained with “masked language model” objective [6] on large language corpus outperforms on majority NLP tasks. Furthermore, Su et al. [130] developed VL-BERT, a pre-trainable generic representation for visual-linguistic tasks. In VLN territory, Pre-training approaches are used in two aspects: 1) used pre-trained models to solve VLN tasks, 2) pre-trained VL or VLN models on VLN tasks. For 1): In Li et al. [131], an agent is trained with pre-trained language models, (i.e., BERT [129] and GPT-3 [132]) and stochastic sampling to generalize well in the unseen environment. Hao et al. [133] developed a generic PRE-trained Vision And Language Based Navigator (PREVALENT) agent is pre-trained with image-language-action triples, and fine-tuned on the R2R task. Based on the use of the PREVALENT model, the agent can better complete the task in an unseen environment. Since the pre-training model usually has massive parameters, the efficiency of using it will be relatively low. For reducing the scale of pre-train model and improve the efficiency of inference, Huang et al. [134] introduced two lightweight method, i.e., factorization and parameter sharpening based on the PREVALENT [133] model. For 2): Due to the limitation of training data in VLN task, Majumdar et al. [135] tried to use massive web-scraped resources to address this issue. Therefore, VLN-BERT is proposed and prove that pre-training it on image-text pairs from the network before fine-tuning the specific path instruction data significantly improves the performance of VLN task. Hong et al. [136] proposed a VLN○BERT, which is a multi-modal BERT model equipped with a time-aware recurrent function to provide the agent with richer information. Qi et al. [137] proposed an Object-and-Room Informed Sequential BERT (ORIST) to improve the language grounding performance by encoding visual and instruction inputs at the same fine-grained level, i.e., objects and words. Besides, the trained model can recognize the relative direction of each navigable location and the room type of its current and final navigation target.

**Other Related Research.** To assess the implications of this work for robotics, Anderson et al. [138] transfer a VLN
agent trained in simulation to a physical robot. There is a big difference between high-level discrete action space learned by the agent and robot’s low-level continuous action space. In order to address this issue, they introduced a sub-goal model to identify nearby navigable points and use domain randomization to reduce visual domain differences. With the slow-down performance improvements in VLN tasks, a series of diagnostic experiments were carried out in [139] to reveal the agent’s key points in the navigation process. The results show that the indoor navigation agent will refer to the object mark and direction mark in the instruction when making a decision. When it comes to visual and verbal alignment, many models claim that they can align object marks with certain visual targets, but there are still doubts about the reliability of this alignment.

4) Model Performance Comparison: A table comparing all models in R2R task. The state-of-the-art method is REM, since it is the effective combination of pre-trained backbone model (VLN:©BERT) and data augmentation, making REM model the best existing approach on VLN benchmark.

B. Variations of R2R task

1) Room-for-Room, Room-6-Room, Room-8-Room: Due to the process by which the data are generated, all R2R reference paths are shortest-to-goal paths. There is a certain contradiction between following on instructions and reaching the destination. For properly evaluating consistency, dataset is supposed to be larger and has more diverse reference paths. To address the lack of path variety, Jain et al. [30] proposed a data augmentation strategy that generate longer and more tortuous paths without additional human or low-fidelity machine annotation, which is a new and more challenging dataset, Room-for-Room (R4R).

Inspired by Room-for-Room, [32] created several datasets of longer navigation tasks, Room-6-Room (i.e., R6R) and Room-8-Room (i.e., R8R).

2) Room-to-Room with Continuous Environment: In traditional VLN task, agents operate on a fixed topology of traversable nodes instead of moving freely in the environment. Krantz et al. [33] proposed Vision-and-Language Navigation in Continuous Environments (VLN-CE) task, where agents can move freely in the environment rather than transporting between pre-defined navigable points. This setup introduces many challenges that were ignored in previous work. The VLN-CE codebase and baseline models are available.

Chen et al. [142] proposed a modular approach to VLN using topological maps, since the conventional end-to-end approaches are struggle in freely traversable environments. They decomposed VLN-CE tasks in two stages: Planning and Control. During the exploration, topological map representation is built and used for navigation plan stage. A local controller receives the navigation plan and generates low-level discrete action. Wang et al. [143] pointed out that different robots often equipped with various camera configurations, these differences make it difficult to directly transfer the learned navigation skill between robots. Consequently, a generalization strategy is proposed for visual perception based on meta-learning, which enables the agent to quickly adapt to a new camera configuration through few shots learning.

3) Room-Across-Room, Cross Lingual R2R: Ku et al. [31] introduced Room-Across-Room (RxR), a multilingual extension of R2R containg English, Hindi, and Telugu. Besides, the length and number of paths and instruction in this dataset are larger than original R2R. Each instruction word is time-aligned to the virtual poses of instruction creators and validators.

The size, scope and detail of RxR has dramatically expands comparing with R2R dataset, which contains 126K instructions covering 16.5K sampled guide paths and 126K human follower demonstration paths. The dataset is available.

Yan et al. [34] collected a Cross-Lingual R2R dataset, which extends the original benchmark with corresponding Chinese instructions. Then they proposed a principled meta-learning method that dynamically utilizes the augmented machine translation data for zero-shot cross-lingual VLN.

C. Street View Navigation

Existing works have mainly focused on relatively simple visual input, and the environments are indoor mostly. Actually, the complexity and diversity of the visual input these environments provide are limited, since the challenges of language and vision have been simplified. Therefore, many researchers are interested in outdoor navigation based on Google Street View.

1) Touchdown: Chen et al. [35] introduced Touchdown, a dataset for natural language navigation and spatial reasoning using real-life visual observations. They define two tasks (i.e., navigation and spatial description resolution) that require addressing a diverse set of reasoning and learning challenges. This is the first large scale outdoor VLN task.

The agent receives a 360°RGB panorama when it moves to every navigable point, which is connected with undirected navigation graph. The environment includes 29,641 panoramas and 61,319 edges from New York City. The environment and data are available.

Xiang et al. [144] focused on endowing agent with recognizing and stopping at the correct location in complicated outdoor environments. They introduced a Learning to Stop module to address the issues, which is a simple and model-agnostic module that can be facely added into other VLN models to improve their navigation performance.

For facilitating the experiment, Zhu et al. [145] divided the original StreetLearn dataset into a small part, i.e., Manh-50, which mainly covers the Manhattan area with 31K training data. In addition, a baseline Multimodal Text Style Transfer learning approach is proposed to generate style-modified instructions for external resources and address the data scarcity issue.

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12R2R-to-R4R code is at https://github.com/google-research/tree/master/r4r
13https://github.com/jacobkrantz/VLN-CE
14https://github.com/google-research-datasets/RxR
15https://touchdown.ai
2) StreetLearn: For improving the end-to-end outdoor VLN research, Mirowski et al. [38] presented Google Street View based environment StreetLearn, which is a egocentric photorealistic interactive outdoor navigation task. Mehta et al. [146] are publicly releasing the 29k raw Street View panoramas needed for Touchdown. These are added to StreetLearn dataset as extra resources. The environment code, baseline agent code, and the dataset are available. Based on this environment, they designed two navigation tasks, i.e., given start point and the coordinates of destination, agents needs to find path themselves; another tasks consisting of natural language navigation instructions and image thumbnails, mimicking Google Maps.

Mirowski et al. [147] using deep reinforcement learning to address outdoor city navigation issue. Based on the image and connectivity on Google Street View, a duel pathway navigation agent is proposed with interactive environment.

3) Other outdoor navigation tasks: StreetNav. StreetNav is a extension of StreetLearn proposed by Hermann et al. [37]. The main difference is in StreetNav, driving instructions from Google Maps by randomly sampling start and goal positions are added to dataset, which likes autonomous driving environment.

Talk to Nav. Vasudevan et al. [148] developed an interactive visual navigation environment based on Google Street View named Talk2Nav dataset with 10,714 routes, and an built effective model to create large-scale navigational instructions over long-range city environments.

Street View. Based on Google Street View, Cirik et al. [149] sampled 100k routes in 10 U.S. cities to build a outdoor instruction following task environment. They argued outdoor navigation is a more challenging task because the outdoor environment is more chaotic and objects are more diverse

D. Other Tasks

1) RUN: Aiming at explaining navigation instructions based on real, dense, and urban map, Paz-Argaman and Tsarfaty [36] proposed a Realistic Urban Navigation (RUN) task, which has 2,515 instructions annotated by Amazon Mechanical Turk.

2) ARRAMON: Kim et al. [39] proposed ARRAMON, which contains two sub-task: object collecting and object referring expression comprehension. During this task, the agent is required to find and collect different target objects one by one through natural language instruction-based navigation in a complex synthetic outdoor environment.

VI. Multi-turn Tasks

Prior work defines agents to navigate in an environment with single-turn instruction. Recently, there is surge of dialog-enabled interactive assistant, where the interaction is often a multi-turn process. In this scenario, the information is asymmetric for guides and navigators. The guide often has perfect knowledge of the environment, the agent, and the task and the agent should be able to ask for assistance and understand the dialogue history.

**TABLE III**

| Leader-Board (Test Unseen) | Single Run | Pre-explore | Beam Search |
|----------------------------|------------|-------------|-------------|
| **Models** | NE↓ | OR↑ | SR↑ | SPL↑ | NE↓ | OR↑ | SR↑ | SPL↑ | TL↓ | SR↑ | SPL↑ |
| Random [1] | 9.79 | 0.18 | 0.17 | 0.12 | - | - | - | - | - | - | - |
| Seq-to-Seq [1] | 20.4 | 0.27 | 0.20 | 0.18 | - | - | - | - | - | - | - |
| Look Before You Leap [116] | 7.5 | 0.32 | 0.25 | 0.23 | - | - | - | - | - | - | - |
| Speaker-Follower [94] | 6.62 | 0.44 | 0.35 | 0.28 | - | - | - | - | 1257 | 0.54 | 0.01 |
| Chasing Ghosts [140] | 7.83 | 0.42 | 0.33 | 0.30 | - | - | - | - | - | - | - |
| Self-Monitoring [97] | 5.67 | 0.59 | 0.48 | 0.35 | - | - | - | - | 373 | 0.61 | 0.02 |
| PTA [105] | 6.12 | 0.50 | 0.43 | 0.38 | 4.21 | 0.67 | 0.61 | 0.59 | 358 | 0.63 | 0.02 |
| Regretful Agent [98] | 5.69 | 0.48 | 0.56 | 0.40 | - | - | - | - | 196.53 | 0.61 | 0.03 |
| FAST [99] | 5.14 | - | 0.54 | 0.41 | - | - | - | - | 687 | 0.69 | 0.01 |
| EGP [104] | 5.34 | 0.61 | 0.53 | 0.42 | - | - | - | - | - | - | - |
| ALTR [100] | 5.49 | - | 0.48 | 0.45 | - | - | - | - | - | - | - |
| Environmental Dropout [114] | 5.23 | 0.59 | 0.51 | 0.47 | 3.97 | 0.70 | 0.64 | 0.61 | - | - | - |
| SERL [118] | 5.63 | 0.61 | 0.53 | 0.49 | - | - | - | - | - | - | - |
| OAAM [111] | - | 0.61 | 0.53 | 0.50 | - | - | - | - | - | - | - |
| CMG-AAL [103] | 4.61 | - | 0.57 | 0.50 | - | - | - | - | - | - | - |
| AuxRN [101] | 5.15 | 0.62 | 0.55 | 0.51 | 3.69 | 0.75 | 0.68 | 0.65 | - | - | - |
| DASA [128] | 5.11 | - | 0.54 | 0.52 | - | - | - | - | - | - | - |
| ReyGraph [109] | 4.75 | - | 0.55 | 0.52 | - | - | - | - | - | - | - |
| ORIST* [137] | 5.10 | - | 0.57 | 0.52 | - | - | - | - | - | - | - |
| PRESS* [141] | 4.53 | - | 0.57 | 0.53 | - | - | - | - | - | - | - |
| PRRAVLENT* [133] | 4.53 | - | 0.57 | 0.53 | - | - | - | - | - | - | - |
| NvEM [126] | 4.37 | - | 0.58 | 0.54 | - | - | - | - | - | - | - |
| SSM [112] | 4.57 | 0.70 | 0.61 | 0.46 | - | - | - | - | - | - | - |
| VLN*:BERT [136] | 4.09 | - | 0.63 | 0.57 | - | - | - | - | - | - | - |
| Active Exploration [102] | 4.33 | 0.71 | 0.60 | 0.41 | - | - | - | - | - | - | - |
| REM(Based on VLN*:BERT) [127] | 3.87 | 0.65 | 0.59 | - | - | - | - | - | - | - | - |

**Table III** Leaderboard results comparing all models on test split in unseen environments. We compare three training settings: Single Run (without seeing unseen environments), Pre-explore (fine-tuning in unseen environments), and Beam Search (comparing success rate regardless of TL and SPL). The primary metric for Single Run and Pre-explore is SPL, while the primary metric for Beam Search is the success rate (SR). We only report two decimals due to the precision limit of the leaderboard. ⋆ means using pre-training method.

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16http://streetlearn.cc
A. Imperative task

In imperative task, the agent can only accept instructions, which are issued in multiple rounds.

1) CEREALBAR: CEREALBAR [40] simulates a scenario, where a leader and a follower collaboratively select cards to earn points. If valid set of card is collected, the players can earn a point.

The leader has full observability on the map, plausible to plan the path for the follower and gives instruction to direct the way. The follower only sees a first-person view of the environment, and requiring instructions to be sensible from the follower’s perspective. The follower cannot respond to the leader. The performance is measured by correct execution of instructions and the overall game reward.

To solve this task, Suhr et al. [40] introduced a learning approach focused on recovery from cascading errors between the sequential instructions, and modeling methods to explicitly reason about instructions with multiple goals.

2) HANNA: HANNA [42] defines a task for a human to find objects in an indoor environment. In this process, the human can ask a mobile agent via natural language. The task is a high-level command (“find [object(s)]”), modeling the general case when the requester does not need know how to accomplish a task when requesting it. HANNA uses the Matterport3D simulator [1] to photo-realistically emulate a first-person view while navigating in indoor environments.

To address the HANNA problem, Nguyen and III [42] developed a hierarchical decision model via a memory-augmented neural agent. Imitation learning is used to teach the agent to avoid past mistakes and make future progress.

3) VNLA: Based on Matterport3D simulator [1], Nguyen et al. [41] introduces the VNLA (Vision-based Navigation with Language-based Assistance) task, where an agent has visual perception in a photo-realistic indoor environment and is guided to find objects in the environment via instructions.

Furthermore, they construct ASKNAV, a dataset for the VNLA task. After filtering out labels that occur less than five times, 289 object labels and 26 room labels were obtained. The data point was defined as a tuple (environment, start pose, goal viewpoints, end-goal). Nguyen et al. [41] also develops a general framework with imitation learning to extend the general framework for indirect intervention.

B. Interactive task

In comparison, human often adopts interactive task more than imperative task, where both the guides and the navigators can ask questions and share information.

1) Talk The Walk: de Vries et al. [45] introduces a navigation task for tourist service and construct a large-scale dialogue dataset, “Talk The Walk”. The tourist is located in a virtual 2D grid environment in New York City and has 360-views of the neighborhood blocks. The guide has an abstracted semantic map of the blocks and the target location is unambiguously shown to the guide from the start. A guide aims to interact with a “tourist” via natural language to help the latter navigate towards the correct location.

de Vries et al. [45] decouples the task of tourist localization from the task and introduces a Masked Attention for Spatial Convolutions (MASC) mechanism to ground the utterances from tourist into the guide’s map.

2) Navigation from Dialog History: Robot navigation in real environments are expected to use natural language to communication and understand human’s meaning. To study this challenge, Thomason et al. [43] introduced CVDN, a human to human dialogues situated in simulated, photorealistic home environments. For training agent to search a goal location in an environment, they define the Navigation from Dialog History (NDH) task. In NDH, an agent is learned to predict navigation actions and find an object given a dialog history between humans in unexplored environments. NDH facilities training agents for navigation, question asking, and question answering. In [43], the authors only concerned the navigation part. To train agents that search an environment for a goal location, they further defined the Navigation from Dialog History task. They formulated a sequence-to-sequence model to encode an entire dialog history to address the NDH task, whose outputs are actions in the environment. Zhu et al. [150] proposed a Cross-modal Memory Network (CMN) to remember the historical information. CMN used a language memory module to learn latent relationships between the current conversation and a dialog history and uses a visual memory module to learns to associate the current visual views and the previous navigation actions. Roman Roman et al. [151] divided multi-turn NDH task into three subtasks: question generation, question answering, and navigation and implement them with three Sequence-to-Sequence models, i.e., a Questioner, a Guide and a Navigator. The progress agents were trained with reward signals from navigation actions, question and answer generation.

3) Just Ask: Base on the Room-2-Room task [1], Chi et al. [44] developed an interactive learning framework to allow the agent to ask for users’ help when needed. And they used reinforcement learning with a proposed reward shaping term as the initial model, which enables the agent to ask questions only when necessary.

4) RobotSlang: Banerjee et al. [46] decouples the cooperative communication task into Localization from Dialog History (LDH) and NDH task, where a driver agent must localize in the global map or navigate towards the next target object according to the visual observations the dialog with the commander. Different from other tasks, the environment, agent are physical, the sensor observations are camera RGB.

Moreover, Banerjee et al. [46] evaluated human performance on the LDH task and created an initial, Sequence-2-Sequence model for the NDH task.

VII. CONCLUSIONS AND DISCUSSIONS

A. Discussions

Although the application of deep learning in the field of VLN has achieved gratifying performance, it is worth noting that it still has limitations in many other aspects. The problems which restrict the performance have not been solved, and the inherent limitations of deep learning also remain unresolved.
Studying how to solve these limitations will be a key issue in the future of this field. Thus, here we will only list limitations which are common to all tasks, and provide possible solutions to these.

1) Poor generalization performance: There are a bunch of variations between VLN datasets, including the resolution of acquisition images, parameter settings, types of objects in the environment, etc. The differences between the datasets challenge the generalization performance of deep learning models. Some of the most advanced models can only perform well on certain dataset, and perform poorly on others. In fact, even focus on one task, the model performance in the seen scenes during training is far greater than the unseen scenes during testing.

To solve this problem, meta-learning is a feasible method because it can share a prior parameter with the minimum average distance from the best parameter of each task in the parameter space. [143] used Model-Agnostic Meta-Learning (MAML) algorithms to improve model generalization in task VLN-CE, which enables the agent to get accustomed quickly to a new camera configuration with a few shots. Another work [152] adopted MAML to learn a self-supervised loss, which can be used in new environments directly without extra training. Besides, Lifelong learning [153], transfer learning [100], curriculum learning [32] and external prior knowledge [90, 154] are introduced to help solving VLN tasks.

Despite the generalization ability of the deep learning model, we argue that another reason is that most models are confused with both unseen environments and unknown objects. When you ask a seven-year-old boy to fetch a laptop from a remote place, he can finish the task even if he does not see the computer over there ever, but there is a potential preliminary that he knows what a computer is. However, in most of the tasks, the environment is unseen, and some objects are unknown. Estimating the navigation ability of an agent under these settings is not rigorous. Therefore, we should solve generalizations on the unseen environment and with unknown objects separately.

2) High consumption of deep learning: Because of the huge size of the network and the amount of parameters, as well as training on large-scale labeled dataset, the VLN model has achieved the current results. The model requires a lot of computing resources and time during training. A model to achieve the best results usually requires multiple GPUs training for several days. VLN-CE has made great improvements, and only needs 60+ hours of training in the case of a single NVIDIA GeForce RTX 2080Ti. Another disadvantage caused by high consumption is to prevent them from being deployed on portable devices, such as small drones [70].

One direction to solve the problem of high consumption in deep learning is to design a more novel network structure and explore operations or layers with low computing load and low memory consumption. For example, the model can be compressed by quantizing the network weight or distill to a light model to reduce the complexity. Other possible solution could be model pruning method and Huffman coding for weights of the model.

3) Lack of interpretability: An important issue in applying visual language navigation to real life is to what extent people accept its "black box", because there may be certain safety hazards. This lack of interpretability is an inherent defect of deep learning. Fortunately, there are several studies focused on this issue. The methods to solve this problem can be divided into generating attention heatmaps, the semantics of heat maps, and other explorations.

Attention heatmaps. The heatmap generated not only provides a cue that how deep learning makes decisions, but also provides guidance and assistance to the language grounding process.

Recent works such as [101, 136] make visualization of certain attention layers in model. They visualized the changes in language attention weights of all instructions during navigation to track navigation progress. As the agent moving in the environment, the attention weights of instructions changes with it. In terms of the attention weight of the visual elements for the direction of choice, it follows a similar pattern, which means that the most relevant part of the instruction is used to guide action selection.

Other explorations. Note that there are several other studies on the topic of interpretability. Zhu et al. [139] paid attention to diagnosing the existing VLN method and tried to figure out what really matters. They conducted extensive ablation studies and got some meaningful conclusions on how the navigation agents understand the multimodal input data. This work made a difference because it encourages more exploration and research to understand the black box of deep learning model and and improve the task setting and future research capabilities of navigation agents.

B. Conclusions

In this survey, we have comprehensively reviewed existing visual-and-language tasks, introduced typical datasets and simulators, summarized newest research progress. We argue that the most important contribution is the new taxonomy:

- All tasks are divided into multi-turn and single-turn depending on when instructions are given.
- The multi-turn tasks can be divided into imperative task and interactive task based on whether the guide and navigator can exchange information
- The single-turn tasks are divide into goal-orientation and route-orientation based on whether instructions specify a route.

We believe that our taxonomy will help to catalog future tasks and also better understand the remaining unresolved problems facing visual-and-language navigation tasks, what is more, to find out some general approaches.

At last, we present some thinking about the future directions of VLN tasks:

1) Compared with single-turn, the multi-turn tasks, especially the interactive task, are more likely to have practical applications. Firstly, a hard task can be decomposed into sub-tasks, each of them are easily to finish. Secondly, it is more in line with actual situation. Instead of trial and error or early stop, people are more likely
to seek help when they are in trouble. Meanwhile, it is simple to establish a remote communication between a guide and a navigator.

2) A variety of perception technologies should be used. Most of the Agents in VLN tasks only equip an optical monocular camera. However, the technology of 3D reconstruction, depth estimation and so on have become more and more mature. And Wijmans et al. [81] have proved that the point cloud perception can help an EQA agent to find the target.

3) Utilize a physical agent to complete the VLN task. Nowadays, some autonomous mobile robots are already in mass production, such as the big dog of Boston Dynamics. What is more, Anderson et al. [138] have used a TurtleBot2 mobile robot equipped with a 2D laser scanner and a 360°RGB camera to finish a VLN task.

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