Towards Versatile Embodied Navigation

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Project page: https://github.com/hanqingwangai/VXN

Abstract

With the emergence of varied visual navigation tasks (*e.g.*, image-/object-/audio-goal and vision-language navigation) that specify the target in different ways, the community has made appealing advances in training specialized agents capable of handling individual navigation tasks well. Given plenty of embodied navigation tasks and task-specific solutions, we address a more fundamental question: *can we learn a single powerful agent that masters not one but multiple navigation tasks concurrently*? First, we propose VXN, a large-scale 3D dataset that instantiates four classic navigation tasks in standardized, continuous, and audiovisual-rich environments. Second, we propose VIENNA, a versatile embodied navigation agent that simultaneously learns to perform the four navigation tasks with one model. Building upon a full-attentive architecture, VIENNA formulates various navigation tasks as a unified, *parse-and-query* procedure: the target description, augmented with four task embeddings, is comprehensively interpreted into a set of diversified goal vectors, which are refined as the navigation progresses, and used as queries to retrieve supportive context from episodic history for decision making. This enables the reuse of knowledge across navigation tasks with varying input domains/modalities. We empirically demonstrate that, compared with learning each visual navigation task individually, our multitask agent achieves comparable or even better performance with reduced complexity.

1 Introduction

As a fundamental research topic, visual navigation has attained extensive attention across many disciplines, including robotics [1], computer vision [2, 3], and natural language processing [4]. Consider a typical navigation scenario (Fig. 1), in which a human intends to direct a robot agent to navigate to a target – a buzzing washer. The target can be specified by a photo of the washer (*i.e.*, ***image-goal nav.*** [5]), or the buzzing sound (*i.e.*, ***audio-goal nav.*** [6]), or the corresponding semantic tag – *washing machine* (*i.e.*, ***object-goal nav.*** [7]), or linguistic instructions – "*go to the end of this corridor, turn left and enter the laundry-room*" (*i.e.*, ***vision-language nav.*** [8]). Naturally, the agent is expected to be smart enough to execute all these kinds of navigation tasks involving varying modalities/domains (*i.e.*, image, audio, semantic tag, text) with different optimal policies. Contrary to our expectation, almost all existing navigation agents are specifically designed/trained for one specific task – a "versatile" agent capable of mastering multiple navigation tasks remains far beyond reach.

Besides its great value in practice, investigating embodied navigation in multitask scenarios can help better understand human intelligence. First, we humans can learn multiple tasks in a parallel ad hoc

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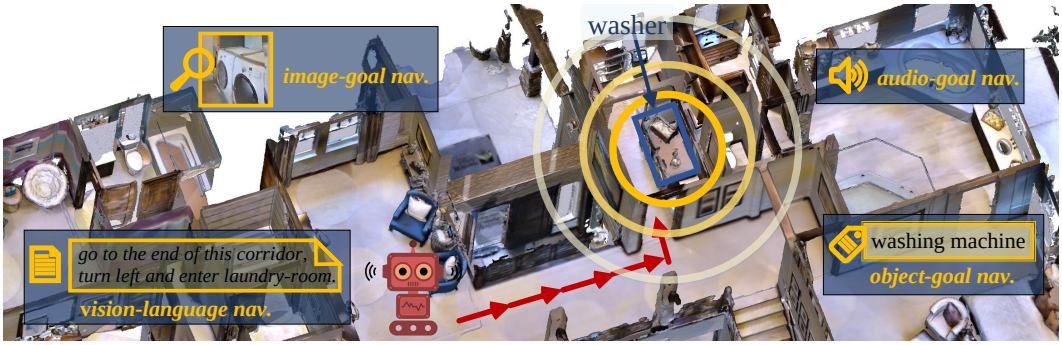


Figure 1: Rather than existing efforts training specialized agents on individual navigation tasks, we build a single powerful agent that can undertake multiple tasks, *i.e.*, *image-goal nav.*, *audio-goal nav.*, *object-goal nav.*, and *vision-language nav.*, in visually and acoustically realistic environments.

manner, and benefit from commonalities across related tasks [9]. Second, we accomplish tasks by processing and combining signals from different modalities. Evidences from cognitive psychology indicate that our senses are functioning together and multisensory integration is a central tenant of human intelligence [10, 11]. Though the idea of multitask learning [12] was widely explored in computer vision field [13], prior attempts are often made in unsupervised and supervised learning settings; in the context of multitask reinforcement learning (MTRL) [14], not much is done for visually-rich, embodied navigation scenarios. One possible reason is the lack of a suitable dataset, compounded by considerable costs involved in data collection, as multiple navigation tasks should be supported.

In response, a large-scale 3D dataset, VXN, is established to investigate *multitask multimodal embodied navigation* in *audiovisual complex* indoor environments. VXN allows simulated robot agents to concurrently learn four tasks, *i.e.*, *image-goal nav.*, *audio-goal nav.*, *object-goal nav.*, and *vision-language nav.*, in continuous, acoustically-realistic and perceptually-rich world[2]. Based on a high-throughput simulator [15], VXN instantiates different navigation tasks in unified environments following the same physical rules. It equips the agents with multimodal sensors to gather information from 360° RGBD and audio observations. Taken all together, VXN provides a realistic testbed for multitask navigation.

With VXN, we further develop VIENNA, a versatile embodied navigation agent that jointly learns to solve the four navigation tasks using *one single model* without switching among different models. Based on Transformer encoder-decoder architecture [16], VIENNA encodes the full episode history of multisensory inputs (*i.e.*, RGB, depth, and audio) and navigation actions, and absorbs common knowledge across different navigation tasks with a shared decoder. Target signals (*i.e.*, goal picture, target class, aural cues, linguistic instruction) are parsed into *queries*, and the supportive context retrieved from the encoded history is fed to corresponding *policy* for task-specific decision making. With such a *fully-attentive* model design, VIENNA is able to comprehend multimodal observations, conduct long-term reasoning, and, more essentially, exploit cross-task knowledge.

By contrasting our VIENNA to several single-task counterparts on VXN, we empirically demonstrate **i)** *Better performance*. Through exploiting cross-task relatedness, VIENNA outperforms independent task training. **ii)** *Reduced model-size*. Training four tasks together using a single VIENNA achieves about four times model size compression, compared with training them individually. **iii)** *Improved generalization*. VIENNA performs robust on unseen environments, through learning task-shared, general representations. **iv)** *More is better*. The above conclusions are typically true when we train VIENNA on more navigation tasks. **v)** *Multisensory integration does matter*. Both visual (RGB and depth) and aural information are crucial building blocks for general-purpose navigation robot creation.

2 Related Work

Embodied Navigation. As a fundamental element in building intelligent robots, navigation has long been the focus of the scientific community [17]. The availability of building-scale 3D datasets [18–21]

[2]Strictly speaking, as we synthesize visually and acoustically realistic environments, the classic *image-goal nav.*, *object-goal nav.*, and *vision-language nav.* tasks in our VXN dataset are extended as *image-goal visual-audio nav.*, *visual-audio object-goal nav.*, and *visual-audio-language nav.*, respectively.

and high-performance simulation platforms [15, 22–24] led to a plethora of reproducible research of navigation in large-scale, visually-rich environments. Depending on how to specify the target goal, diverse navigation tasks are proposed to let an agent **i)** navigate to target coordinates (*point-goal nav.* [15]), **ii)** find an instance of a given object category (*object-goal nav.* [7]), **iii)** search for target photos (*image-goal nav.* [5]), **iv)** locate sound sources (*audio-goal nav.* [6]), or **v)** follow navigation instructions (*vision-language nav.* [8, 25]). Aside from these battlefields, there are some more complicated embodied tasks, such as *embodied question answering* [26], *vision-dialog nav.* [27–29], and *multiagent nav.* [30]. The community also made great strides in improving reinforcement learning (RL) algorithms capable of fulfilling specific navigation tasks, by using, for example, recurrent neural networks [8, 15, 31], map building [3, 32–41], path planning [42–44], cross-modal attention [41, 45–48], synthesized or unlabeled data [49–54], and external knowledge [7, 55]. However, though the learning algorithm is general – RL, each solution is not; each navigation agent can only handle the one task it was trained on.

With various navigation tasks and task-specific navigation solutions, a critical question arises *whether we can build a single general agent that works well for multiple navigation tasks*. In response, we make two unique contributions. First, we build a large-scale 3D dataset that supports four representative navigation tasks in continuous and realistic environments. In contrast, prior navigation datasets are built upon different platforms and with certain assumptions/configurations (*e.g.*, sparse navigation graphs [8], discrete world representation [6]), making them hard to explore different navigation tasks in unified and standardized environments. Second, we create a generalist agent which is capable of undertaking a set of navigation tasks of different modalities/domains, and is equipped with multimodal sensors (*i.e.*, RGB, depth, audio) to better address real-world scenarios. However, existing navigation agents are trained one task at the time, each new task requiring to train a new agent instance.

Multitask Learning (MTL). MTL [12], inspired by the human ability to transfer knowledge across different tasks [56], has led to wide success in computer vision [57–59] and natural language processing [60]. Related efforts were made along three directions [13]: **i)** *architecture design* (*i.e.*, how to partition the model into task-specific and shared components) [61–64], **ii)** *optimization* (*i.e.*, how to balance learning between different tasks) [65–70], and **iii)** *task relationship learning* (*i.e.*, how to learn and utilize task relationships to improve learning) [71–73]. In the field of MTRL [74–80], recent solutions explored knowledge transfer [81], modular networks [82, 83], and policy distillation [84, 85]. A few robotics benchmarks [86–88] are also proposed for MTRL. However, most of these efforts were based upon low-dimension observations, *e.g.*, grid-world like or game environments. To the best of our knowledge, there are two prior work [47, 89] that addressed multitask navigation, but they only consider two closely-related, language-guided navigation tasks with the same input modalities.

Drawing inspiration from these efforts, we seek for a "universal" agent that can complete multiple navigation tasks with a single agent instance, and distinguish ourselves by **i)** joint learning of four navigation tasks with diverse input modalities, **ii)** visually complex and acoustically realistic operation space, **iii)** multisensory integration, and **iv)** fully-attentive architecture based parse-and-query regime.

Auxiliary Learning in Embodied Navigation. There are a group of algorithms that exploit complementary objectives from auxiliary tasks to facilitate navigation policy learning. Specifically, *supervised auxiliary tasks* expose privileged information to the agent (*e.g.*, depth [90], surface normals [91], semantics [26], *etc.*). *Self-supervised auxiliary tasks* derive free supervisory signals from the agent's own experience (*e.g.*, next-step visual feature prediction [92], predictive modeling [93], loop closure prediction [90], temporal distance estimation [94], navigation progress estimation [95, 96], *etc.*).

Although auxiliary learning based navigation models are also trained on a set of tasks, their ideas are far away from ours. These models still focus on only a single "main" navigation task with extra aid of auxiliary intermediate objectives, while we aim to capture and utilize common knowledge of a collection of different navigation tasks to enhance the performance on all the tasks. Moreover, their auxiliary tasks, in principle, can be utilized by our agent, but they cannot handle our task setting.

Transformer in Embodied Navigation and MTL. Inspired by the great success of Transformer [16] in sequence transduction tasks, a few recent methods applied Transformer for certain navigation tasks [40, 97–101]. Rather than sharing similar advantages in long-term memory and cross-modal information fusion, our method further formulates different navigation tasks as a unified process of active goal parsing and supportive information query. Through cleverly encoding all task-specific embeddings into goal parsing, our agent is able to explicitly leverage cross-task knowledge to boost different navigation tasks. There are also a few notable studies that exploit Transformer-like network architectures for MTL [102–105], while none of them addresses embodied visual tasks.

Table 1: Data splits and the number of navigation episodes in our VXN dataset (§3.2).

Navigation Task	train (58 environments)	val seen (58 environments)	val unseen (11 environments)
Audio-goal	2.0M episodes	500 episodes	500 episodes
Vision-language	10,819 episodes	778 episodes	1,839 episodes
Object-goal	2.6M episodes	500 episodes	2,195 episodes
Image-goal	5.0M episodes	495 episodes	495 episodes
Total	9.6M episodes	2,273 episodes	5,029 episodes

Table 2: Comparison (§3.2) of navigation datasets (MT: multitask; CS: continuous space; VR/AR: visual/audio realistic; PA: panorama).

Navigation Dataset	Year	MT	CS	VR	AR	PA
EQA [26]	2018					
Habitat-PointGoal [15]	2019		✓	✓		
R2R [8]	2018			✓		
VLN-CE [25]	2020		✓	✓		
Gibson-ImageGoal [3]	2020		✓	✓		✓
SoundSpaces [6]	2020			✓	✓	
VXN	2022	✓	✓	✓	✓	✓

Pretraining in Embodied Navigation. A series of methods decompose embodied tasks into visual (and linguistic) representation learning and policy training [52, 91, 106–108]. They pretrain a general model on easily-acquired viual or multimodal data (*e.g.*, image captions) and fine-tune the policy for "downstream" navigation tasks. Though showing improved generalization and transfer abilities, the result is still a collection of independent task-specific models rather than a single agent instance.

3 VXN Dataset for Multitask Multimodal Embodied Navigation

3.1 Task Collection and Dataset Acquisition

VXN includes four famous navigation tasks, *i.e.*, *image-goal nav.* [5], *audio-goal nav.* [6], *object-goal nav.* [7], and *vision-language nav.* [8]. These tasks are with different input modalities/domains (*i.e.*, visual, audio, semantic tag, and language); their original datasets adopt different world representations (*i.e.*, graph based [8] *vs* discrete [6] *vs* continuous [15]), environment configurations (*i.e.*, visually poor [22] *vs* perception rich [8] *vs* audiovisual realistic [6]), and success criteria (*i.e.*, 3 m [8] *vs* 1 m [5] *vs* 1 m [7] *vs* 1 m [99]). Hence, to study these four tasks in a single learning system, it is desired to build a standardized dataset that initiates them with similar problem settings, *e.g.*, dynamic transition, world representations, and audiovisual properties, instead of simply combining several single-task navigation datasets together. On the other hand, it is wise to maximize the reuse of existing datasets, ensuring continuity and compatibility w.r.t. former research, and reducing data annotation cost.

As many previous navigation datasets [6, 8, 109] are built upon Matterport3D (MP3D) [19] environments and Habitat [15] simulator, we derive a unified, multitask navigation dataset – VXN – by converting previous *task-specific* datasets to *standardized, continuous, audiovisual-rich environments*:

- Our ***audio-goal nav.*** is built upon SoundSpaces [6], which offers audio renderings for MP3D and allows to navigate sounding targets, or conduct point navigation with extra aid of audio cues. Due to heavy acoustic simulation cost, [6] uses a grid-based world model: it samples room impulse res- ponse over a discrete, horizontal plane (1.5 m above the floor with 0.5 m$\times$0.5 m grid size). We devise an audio simulator to efficiently transfer grid-level audio renderings into continuous setting (*cf.* §3.2).
- Our ***vision-language nav.*** is built upon R2R [8], which labels MP3D with linguistic navigation instructions. R2R is yet bounded to graph-based world representation – each scene can be only observed from a few fixed points ($\sim$117) and environment topologies are pre-given. We use [25] to convert R2R to the continuous setting, and then adopt [6] and our audio simulator for audio rendering.
- Our ***image-goal nav.*** is built upon Habitat [15] ImageNav repository [110], which is for photo target guided navigation in MP3D environments. Again, continuous audio rendering is made.
- Our ***object-goal nav.*** is built upon Habitat2020 ObjectNav challenge [109], which requires an agent to navigate a MP3D environment to find an instance of an object class. A total of 21 visually well defined object categories (*e.g.*, *chair*) are considered and audio rendering is also made; but the GPS + Compass sensor, used in [109], is not adopted in VXN, for formalizing different task settings.

3.2 Task Setting and Dataset Design

Panoramic Visual Simulator. With Habitat API, 360° egocentric RGBD view is rendered at 300 fps.

Audio Simulator. With [6], ambisonics are generated at locations sampled in MP3D scenes and converted to binaural audio [111], *i.e.*, an agent emulates two human-like ears. To synthesize continuous auditory scenes, we use [112] for real-time binaural room impulse responses (BRIRs) interpolation. We adopt Dynamic Time Wrapping [113] to temporally align left and right ear BRIRs and then map

the warped *interpolated* vectors back into the "unwarped" time domain, to get BRIRs at arbitrary locations and directions. As in [99], the sounds of the 21 object categories [109] in *object-goal nav.* are used for audio rendering. Moreover, the sounds are associated with the objects of same semantic categories to ensure generating semantically meaningful and contextual audio [99]. For *image-goal nav.*, *object-goal nav.*, and *vision-language nav.*, the audio is used as background sound, which can reveal the geometry of environment [6], complement the visual cues, and make the tasks closer to the real-world. For *audio-goal nav.*, the navigation target is directly specified by the audio.

Episodes and Dataset Splits. In VXN, each episode is defined as a tuple: ⟨scene, audio waveform, agent start location, agent start rotation, goal location, target description⟩. We use the standard 58/11/18 train/val/test split [114] of MP3D environments. Since previous navigation datasets [8, 15, 109] keep test annotations private, we only use train and val environments to create VXN (*cf.* Table 1).

Action Space. We adopt a panoramic action space, which is widely used in recent embodied robotic tasks [3, 43]. Specifically, the panoramic view is horizontally discreted into a total of 12 sub-views. Agents can move towards a sub-view 0.25 m or stop.

Success Criterion. An episode is considered as successful if the agent **i)** executes stop action, **ii)** within 1 m of the goal location, and **iii)** within a time horizon of 500 actions (as in [15, 91, 115]).

Dataset Features. As shown in Table 2, VXN poses greater challenges: the agent needs to master four navigation tasks with various input modalities in continuous, audiovisual complex environments, mine cross-task knowledge, and reason intelligently about all the senses available to it (RGB, depth, audio).

4 Our Approach

Problem Statement. In *single-task navigation*, an agent learns to reach a goal position. This is typically formulated in a RL framework that solves a partially observable Markov decision process [116]: a tuple $(\mathcal{S}, \mathcal{A}, \mathcal{G}, O, P, R, \gamma)$, where $\mathcal{S}$, $\mathcal{A}$, $\mathcal{G}$ are sets of *states*, *actions* and *targets*, $o_t = O(s_t)$ denotes the local observation at global state $s_t \in \mathcal{S}$ at epoch (decision step) t, $P(s_{t+1}|s_t, a_t)$ is the transition probability from s_t to s_{t+1} given action $a_t \in \mathcal{A}$, $R(s, a) \in \mathbb{R}$ gives the *reward*, and $\gamma \in (0, 1)$ discounts future rewards. The agent uses a *policy* $\pi(a|o, g)$ to produce its action a, conditioned on its local observation o and target goal $g \in \mathcal{G}$, and optimizes its accumulated discounted reward $J = \sum_{t'=t}^{T} \gamma^{t'-t} R(s_{t'}, a_{t'})$.

In our *multitask navigation*, a single agent needs to master $K=4$ tasks, *i.e.*, {*audio-goal*, *object-goal*, *image-goal*, *vision-language*} in VXN environments. We formalize this as a MTRL problem: $\{(\mathcal{S}, \mathcal{A}, \mathcal{G}_k, O, P, R_k, \gamma_k)\}_{k=1}^{K}$, where the agent concurrently learns K task-specific policies $\pi_{1:K}$ that maximize the rewards $J_{1:K}$. The single multitask agent is expected to exploit cross-task knowledge to achieve close or better navigation performance on the K tasks, compared with training K single-task agents individually.

Transformer Preliminary. The core of Transformer [16] is an attention function (denoted as f_{ATT}), which takes a query sequence $\boldsymbol{x} \in \mathbb{R}^{n \times d}$ and a context sequence $\boldsymbol{y} \in \mathbb{R}^{m \times d}$ as inputs, and outputs:

$$\tilde{\boldsymbol{y}} = f_{\text{ATT}}(\boldsymbol{x}, \boldsymbol{y}) = \text{softmax}\big((\boldsymbol{x}\boldsymbol{W}^q)(\boldsymbol{y}\boldsymbol{W}^k)^\top / \sqrt{d}\big)\big(\boldsymbol{y}\boldsymbol{W}^v\big). \tag{1}$$

where $\tilde{\boldsymbol{y}} \in \mathbb{R}^{n \times d}$ is with the same length n and embedding dimension d as $\boldsymbol{x}$, and $\boldsymbol{W}^{q,k,v} \in \mathbb{R}^{d \times d}$ are learnable *query*, *key*, and *value* projection matrices, respectively. Note that Eq. 1 is applicable to both *self-attention* in Transformer encoder (*i.e.*, $\boldsymbol{x} \equiv \boldsymbol{y}$), and *cross-attention* in Transformer decoder (*i.e.*, $\boldsymbol{x} \neq \boldsymbol{y}$). Further, each Transformer layer block can be given as:

$$\boldsymbol{x}' = \boldsymbol{x} + f_{\text{MHA}}(\boldsymbol{x}, \boldsymbol{y}) \in \mathbb{R}^{n \times d}, \qquad \boldsymbol{z} = \boldsymbol{x}' + f_{\text{MLP}}(\boldsymbol{x}') \in \mathbb{R}^{n \times d}, \tag{2}$$

where f_{MHA} refers to a *multi-head attention* layer, derived by computing several f_{ATT} in parallel, and f_{MLP} is multi-layer perceptron. The layer normalization is omitted for brevity.

Core Idea. Built upon a Transformer encoder-decoder architecture, our VIENNA unifies the four VXN tasks as an attention-based, *parse-and-query* framework: the target description $g \in \mathcal{G}_k$ is *online* parsed into a set of embeddings, which are used to "query" the encoded episode history; the retrieved supportive cues are fed into the corresponding policy π_k for decision making. To better handle multiple tasks, VIENNA **i)** learns task-wise context and involves all the task-specific embeddings into target parsing, **ii)** shares representations among tasks, **iii)** lets task-specific policies $\pi_{1:K}$ reuse knowledge, and **iv)** trains the polices via a multitask version of Distributed Proximal Policy Optimization (DPPO) [117].

VIENNA has three modules (*cf.* Fig. 2): **i)** an *episodic encoder* (§4.1) that fuses multisensory cues and encodes the full episode history of navigation; **ii)** a *target parser* (§4.2) that actively interprets the

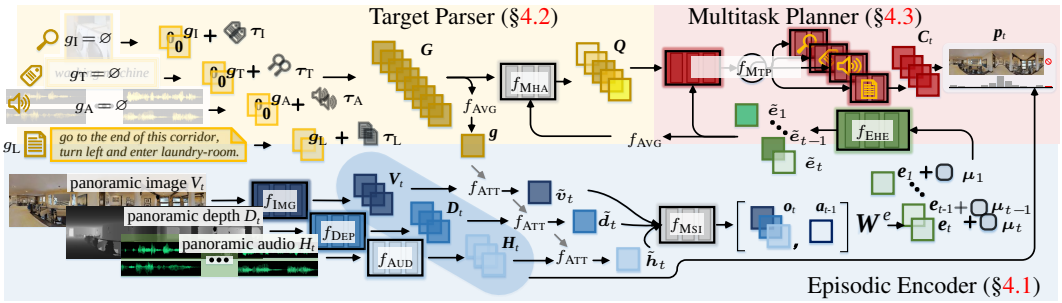


Figure 2: Detailed network architecture of VIENNA, at epoch t in a *vision-language nav.* episode.

target specification into several embeddings; and **iii)** a *multitask planner* (§4.3) that uses the target embeddings to query encoded episodic history and leverages the returned context for action prediction.

4.1 Episodic Encoder

At the start of each episode, VIENNA receives a target description $g \in \{$goal image, target sound, target class, language instruction$\}$ and derives an embedding vector $\boldsymbol{g} \in \mathbb{R}^d$ (detailed in §4.2). At each epoch t, VIENNA has a 360° egocentric audiovisual perception o_t, *i.e.*, RGB+depth+audio, of its surrounding.

Intra-Modal Encoders. A *visual encoder* f_{IMG} maps perceived panoramic image $V_t \in \mathbb{R}^{12\times224\times224\times3}$ into visual features $\boldsymbol{V}_t = [\boldsymbol{v}_{1,t}, \cdots, \boldsymbol{v}_{12,t}] \in \mathbb{R}^{12\times d}$, where $\boldsymbol{v}_{i,t} \in \mathbb{R}^d$ is the feature vector of i-th sub-view in V_t. Similarly, a *depth encoder* f_{DEP} and an *audio encoder* f_{AUD} map the perceived panoramic depth image $D_t \in \mathbb{R}^{12\times256\times256\times1}$ and spectogram tensor of binaural sound (collected over 12 horizontal directions) $H_t \in \mathbb{R}^{12\times41\times44\times2}$ into depth and audio features, *i.e.*, $\boldsymbol{D}_t = [\boldsymbol{d}_{1,t}, \cdots, \boldsymbol{d}_{12,t}] \in \mathbb{R}^{12\times d}$, and $\boldsymbol{A}_t = [\boldsymbol{a}_{1,t}, \cdots, \boldsymbol{a}_{12,t}] \in \mathbb{R}^{12\times d}$, respectively.

Target-Guided Cross-Modal Encoder. With the target description vector $\boldsymbol{g} \in \mathbb{R}^d$, cross-attention f_{ATT} (*cf.* Eq. 1) is separately applied over $\boldsymbol{V}_t$, $\boldsymbol{D}_t$, and $\boldsymbol{H}_t$ to assemble target-related sensory information:

$$\tilde{\boldsymbol{v}}_t = f_{\text{ATT}}(\boldsymbol{g}, \boldsymbol{V}_t) \in \mathbb{R}^d, \quad \tilde{\boldsymbol{d}}_t = f_{\text{ATT}}(\boldsymbol{g}, \boldsymbol{D}_t) \in \mathbb{R}^d, \quad \tilde{\boldsymbol{h}}_t = f_{\text{ATT}}(\boldsymbol{g}, \boldsymbol{H}_t) \in \mathbb{R}^d. \tag{3}$$

Then $\tilde{\boldsymbol{v}}_t$, $\tilde{\boldsymbol{d}}_t$, and $\tilde{\boldsymbol{h}}_t$ are concatenated for attention based *multisensory information integration* (MSI):

$$\boldsymbol{o}_t = f_{\text{MSI}}([\tilde{\boldsymbol{v}}_t, \ \tilde{\boldsymbol{d}}_t, \ \tilde{\boldsymbol{h}}_t]) \in \mathbb{R}^{3\times d}, \tag{4}$$

where f_{MSI} is achieved by stacking two self-attention based Transformer blocks (*cf.* Eq. 2).

Episodic History Encoder. At epoch t, the multimodal observation embedding $\boldsymbol{o}_t \in \mathbb{R}^{3\times d}$ and latest navigation action embedding $\boldsymbol{a}_{t-1} \in \mathbb{R}^d$, are together projected into a compact "*navigation token*":

$$\boldsymbol{e}_t = [\boldsymbol{o}_t, \boldsymbol{a}_{t-1}]\boldsymbol{W}^e \in \mathbb{R}^d. \tag{5}$$

All the past navigation tokens, $\boldsymbol{e}_{1:t}$, summed with corresponding epoch embedding vectors, $\boldsymbol{\mu}_{1:t} \in \mathbb{R}^d$, are collected into a sequence and fed into an *episode history encoder* (EHE) to get contextualized history representation:

$$[\tilde{\boldsymbol{e}}_1, \cdots, \tilde{\boldsymbol{e}}_t] = f_{\text{EHE}}([\boldsymbol{e}_1 + \boldsymbol{\mu}_1, \cdots, \boldsymbol{e}_t + \boldsymbol{\mu}_t]), \tag{6}$$

where f_{EHE} is implemented as four self-attention based Transformer blocks (*cf.* Eq. 2). In this way, VIENNA is able to store and access its entire episode history of audiovisual observations and actions, leading to persistent memorization and long-term reasoning. The attended history representation $\tilde{\boldsymbol{e}}_{1:t}$ will serve as informative context for predicting the navigation action a_t at epoch t (detailed in §4.3).

4.2 Target Parser

VIENNA is equipped with a *target parser* that actively interprets the

Figure 3: Attention visualization of online target parsing (Eq. 8).

target g (no matter it is specified as a photo g_I, sound g_A, semantic tag g_T, or linguistic instruction g_L) as a group of target embeddings, conditioned on the progress of the navigation episode. Guided by the online created target embeddings, valuable context are selected from episodic experiences $\tilde{\boldsymbol{e}}_{1:t}$ for flexible decision-making. VIENNA thus formulates various navigation tasks in a unified scheme, allowing to exploit cross-task knowledge.

In *image-goal nav.*, a goal image $g_I \in \mathbb{R}^{224\times224\times3}$ is given and embedded as $\boldsymbol{g}_I = f_{\text{IMG}}(g_I) \in \mathbb{R}^{N_I\times d}$. In *audio-goal nav.*, the target is signaled by the binaural sound, *i.e.*, $g_A = H_t \in \mathbb{R}^{12\times41\times44\times2}$ and $\boldsymbol{g}_A = \boldsymbol{H}_t = f_{\text{AUD}}(H_t) \in \mathbb{R}^{N_A\times d}$. In *object-goal nav.*, the target is specified by a semantic tag $g_T \in \{\text{table}, \text{bed}, \cdots\}$, and embedded into a class vector $\boldsymbol{g}_T \in \mathbb{R}^{1\times d}$. In *vision-language nav.*, a language-based trajectory instruction g_{L} is given and mapped into a sequence of word vectors $\boldsymbol{g}_L \in \mathbb{R}^{N_L\times d}$ by a bi-LSTM. At the start of each episode, we first build an *augmented target description embedding* $\boldsymbol{G} \in \mathbb{R}^{4N_G\times d}$:

$$\boldsymbol{G} = \left[\boldsymbol{g}'_I + [\boldsymbol{\tau}_I]^{N_G},\ \boldsymbol{g}'_A + [\boldsymbol{\tau}_A]^{N_G},\ \boldsymbol{g}'_T + [\boldsymbol{\tau}_T]^{N_G},\ \boldsymbol{g}'_L + [\boldsymbol{\tau}_L]^{N_G}\right], \tag{7}$$

where $N_G = \max(N_I, N_A, 1, N_L)$, $\boldsymbol{\tau}_{I,A,T,L} \in \mathbb{R}^d$ are learnable task embedding vectors, and $[\cdot]^{N_G}$ copies its input N_G times. Assuming VIENNA is in an *image-goal nav.* episode, we have $\boldsymbol{g}_I = f_{\text{IMG}}(g_I) \in \mathbb{R}^{N_I\times d}$, and $\boldsymbol{g}_A = [\boldsymbol{0}]^{N_A\times d}$, $\boldsymbol{g}_T = [\boldsymbol{0}]^{1\times d}$, $\boldsymbol{g}_L = [\boldsymbol{0}]^{N_L\times d}$. We pad $\boldsymbol{g}_{I,A,T,L}$ to a unified length N_G, by replication, so as to get $\boldsymbol{g}'_{I,A,T,L}$ and make them contribute equally to $\boldsymbol{G}$. We collect all the task-type embeddings $\boldsymbol{\tau}_{I,A,T,L}$ and current target description $g \in \{g_I, g_A, g_T, g_L\}$ into $\boldsymbol{G}$. In §4.3, we will show this strategy is essential for making use of cross-task knowledge. The target description vector $\boldsymbol{g} \in \mathbb{R}^d$ used in Eq. 3 is given as: $\boldsymbol{g} = f_{\text{AVG}}(\boldsymbol{G})$, where f_{AVG} stands for the average pooling operation.

At epoch t, the target parser comprehends the augmented target description embedding $\boldsymbol{G}$ as a set of N compact embeddings on-the-fly, conditioned on its episodic, contextualized history encoding $\tilde{\boldsymbol{e}}_{1:t}$:

$$\boldsymbol{Q}_t = [\boldsymbol{q}_t^1, \cdots, \boldsymbol{q}_t^N] = f_{\text{MHA}}(f_{\text{AVG}}(\tilde{\boldsymbol{e}}_{1:t}), \boldsymbol{G}) \in \mathbb{R}^{N\times d}, \tag{8}$$

where f_{MHA} is a N-head attention layer (*cf.* Eq. 2), *i.e.*, explain $\boldsymbol{G}$ in different ways, with consideration of current episodic navigation progress. Each of the target embedding vectors $\boldsymbol{q}_t$ can be viewed as a specific, time-varying goal, used to guide action selection a_t at epoch t. As shown in Fig. 3, given a navigation instruction "*go to the end of this corridor, turn left and* $\cdots$", the agent focuses more on "*go to the end of this corridor*" at the start of the navigation episode. After reaching the end of the corridor, the agent shifts its attention to "*turn left*". Here a collection of N target embeddings $\boldsymbol{q}^{1:N}$ are generated at each epoch t, allowing the agent to capture different aspects of target-related information and making the time-varying goal well-planned. For instance, there may exist several essential landmarks in a goal image, or multiple discriminative audio clips in target-emitted sound; during navigation, the agent should be able to pay attention to all these informative clues simultaneously.

4.3 Multitask Planner

At epoch t, a multitask planner (MTP) uses the diversified target embeddings $\boldsymbol{Q}_t = [\boldsymbol{q}_t^1, \cdots, \boldsymbol{q}_t^N]$ to query the episodic history $\tilde{\boldsymbol{e}}_{1:t}$:

$$\boldsymbol{C}_t = f_{\text{MTP}}([\boldsymbol{q}_t^1, \cdots, \boldsymbol{q}_t^N],\ \ [\tilde{\boldsymbol{e}}_1, \cdots, \tilde{\boldsymbol{e}}_t]), \tag{9}$$

where f_{MTP} is achieved by a four-layer Transformer decoder; the first two layers are shared among the four navigation tasks for capturing task-shared policies, while the last two layers are private for each task for task-specific policy learning. We empirically find such *shared trunk* based MTP design yields better performance than learning task-specific policies individually or just training one single "universal" policy (*cf.* §5.2).

The decision-making is conditioned on the retrieved context $\boldsymbol{C}_t \in \mathbb{R}^{N\times d}$, and the presentations of current multi-modal observations (*cf.* §3.2), including $\boldsymbol{V}_t = [\boldsymbol{v}_{1,t}, \cdots, \boldsymbol{v}_{12,t}] \in \mathbb{R}^{12\times d}$, $\boldsymbol{D}_t = [\boldsymbol{d}_{1,t}, \cdots, \boldsymbol{d}_{12,t}] \in \mathbb{R}^{12\times d}$, and $\boldsymbol{A}_t = [\boldsymbol{a}_{1,t}, \cdots, \boldsymbol{a}_{12,t}] \in \mathbb{R}^{12\times d}$. Specifically, at epoch t, VIENNA makes navigate decision by choosing between the 12 current sub-views, as well as an extra `STOP` action. Given 12 subview action embeddings $\{\boldsymbol{b}_{i,t} \in \mathbb{R}^{3\times d}\}_{i=1}^{12}$, *i.e.*, $\boldsymbol{o}_{i,t} = [\boldsymbol{v}_{i,t}, \boldsymbol{d}_{i,t}, \boldsymbol{h}_{i,t}]$ as well as a `STOP` action embedding, *i.e.*, $\boldsymbol{b}_{13,t} = \vec{0}$, represented as an all-zero vector, VIENNA predicts a probability distribution $\boldsymbol{p}_t = [p_{1,t}, \cdots, p_{13,t}]$:

$$p_{i,t} = \text{softmax}_i(f_{\text{AVG}}(\boldsymbol{C}_t)\boldsymbol{W}^p\boldsymbol{b}_{i,t}) \in [0,1], \qquad \text{where } i \in \{1, \cdots, 13\}. \tag{10}$$

As the task embeddings $\boldsymbol{\tau}_{I,A,T,L}$ are encoded into $\boldsymbol{Q}_t$, which is used to find supportive cues from episodic observations $\tilde{\boldsymbol{e}}_{1:t}$ for long-term reasoning and decision-making, $\boldsymbol{\tau}_{I,A,T,L}$ are essentially

trained as task-wise context – they are sensitive to task-related cues. Thus collecting $\boldsymbol{\tau}_{I,A,T,L}$ into $\boldsymbol{G}$ (*cf.* Eq. 7) enables a clever use of cross-task knowledge. For instance, during *image-goal nav.*, $\boldsymbol{\tau}_A$ can help the agent notice some informative audio signals, $\boldsymbol{\tau}_T$ can alert the agent to visually essential semantics, while $\boldsymbol{\tau}_I$ can be activated by crucial landmarks. Related experiments can be found in §5.2.

4.4 MTRL based Multitask Navigation Training

Reward Design. With standardized VXN environments, VIENNA adopts a same reward function for the four navigation tasks, *i.e.*, $R_1 = \cdots = R_4$. Concretely, $R_{1:4}$ has four terms, *i.e.*, a sparse success reward r_{success}, a progress reward r_{progress}, a slack reward r_{slack}, and an exploration reward r_{explore}. $r_{\text{success}} = 2.5$ is only received at the end of a successful episode. $r_{\text{progress}} = -\Delta_{\text{geo_dist}}$ offers dense signals indicating the progress that an action contributes: $\Delta_{\text{geo_dist}}$ gives the change in geodesic distance to the goal position by performing the action. $r_{\text{slack}} = -10^{-3}$, received at each epoch, penalizes redundant actions. r_{explore} [118] divides each environment into a voxel grid with $2.5\,\text{m} \times 2.5\,\text{m} \times 2.5\,\text{m}$ voxels and rewards the agent for visiting each voxel. r_{explore} is defined as 0.25η, where $\eta = \delta^t/\nu$ is a coefficient that decays as episode epoch t and visited voxel number ν increase, and δ is a decay constant of 0.995.

Multitask Distributed Proximal Policy Optimization. We present a multitask distributed proximal policy optimization (MDPPO) algorithm, which utilizes the power of parallel processing to train MTRL agents in our continuous and large-scale environments. MDPPO is built upon (DPPO) [117], a distributed version of proximal policy optimization (PPO) [119] that bounds parameter updates to a trust region to ensure stability, and distributes the computation over many parallel instances of agent and environment. Similarly, MDPPO has a server-client structure: each client worker has several agent copies that collect experiences from VXN environments, compute and send PPO's gradients to the server; the server worker averages the received gradients, updates the agent, and synchronizes the updated weights with the clients. For balanced multitask learning, *i.e.*, training data in VXN are biased between *vision-language nav.* and other navigation tasks: 10.8K *vs* 2.0∼5.0M episodes (*cf.* Table 1), each client worker is required to build four agent copies corresponding to the four VXN tasks.

4.5 Implementation Detail

Network Architecture. The *visual encoder* f_{IMG} is made as an ImageNet [120]-pretrained ResNet50 [121]. The CNN features are fed into a linear layer for dimension compression and flattened into a feature sequence. Similarly, the *depth encoder* f_{DEP} is a modified ResNet50 CNN. The *audio encoder* f_{AUD}, following [6], is a CNN of conv 8×8, conv 4×4, conv 3×3 and a linear layer, interleaved with ReLU. All the sensory features are combined with orientation embeddings. For the *epoch embedding* $\boldsymbol{\mu}$, we use sinusoidal encoding. For the *target parser*, $N = 5$ target embeddings are generated at each epoch t. We set other hyper-parameters as: d=512, N_I=16, N_L=120, N_G=120.

Training and Test. VIENNA is trained on 32 RTX 2080 GPUs for 180 M frames, costing $4,608$ GPU hours. As in [25], we select the checkpoint for evaluation with the best SR on `val unseen`. For MDPPO, we use four client workers and set the discounted factor γ as 0.99. We use AdamW [122] optimizer with a learning rate of 2.5×10^{-4}. Casual attention [16] is adopted to prevent the prediction at epoch t from the influence of future tokens after t. Once trained, a single instance of VIENNA can conduct the four navigation tasks. As normal, greedy prediction is adopted for action selection.

5 Experiment

In §5.1, we first report comparison results for the four VXN tasks. In §5.2, we conduct diagnostic studies to examine the efficacy of our core model design. More results are put in the ***supplementary***.

Baseline. We test several open-source task-specific navigation methods [2, 5, 6, 25]. Note that [2, 5, 6] are re-trained on VXN, since they use different training data [5], world representation [6] (discrete *vs* continuous), or object categories [2] (6 *vs* 21). For [25], we use its check-point but the success criteria are different (3 m *vs* 1 m). Thus their scores on VXN are different from the original ones. In addition, we consider a `Seq2Seq` agent, which also serves as a standard baseline in [8, 25]: an LSTM planner encodes the episode history and predicts navigation actions in a sequential menner. For all the four tasks, we provide the performance of both the single-task and multitask versions of our VIENNA and `Seq2Seq`. Further, `Random policy`, *i.e.*, choosing actions randomly, is included.

Table 3: Quantitative comparison results (§5.1) on VXN dataset (ST: Single-task; MT: Multitask).

Models	val seen				val unseen			
	SR↑	NE↓	OR↑	SPL↑	**SR**↑	NE↓	OR↑	SPL↑
Random	1.2	14.20	1.9	1.2	1.4	14.14	2.2	1.4
Seq2Seq$_{ST}$	15.1	10.44	19.1	12.6	9.3	12.02	13.9	7.4
Seq2Seq$_{MT}$	15.8	10.21	21.3	13.0	10.2	10.22	15.4	8.5
Zhu *et al.* [5]	17.7	9.67	22.0	13.1	12.0	10.19	16.6	8.9
VIENNA$_{ST}$	19.9	9.52	23.2	13.4	12.6	9.83	17.1	9.5
VIENNA$_{MT}$	**22.1**	**9.43**	**24.2**	**14.1**	**14.3**	**9.66**	**18.5**	**11.1**

(a) *image-goal nav.* (IGN)

Models	val seen				val unseen			
	SR↑	NE↓	OR↑	SPL↑	**SR**↑	NE↓	OR↑	SPL↑
Random	0.0	17.13	0.0	0.0	0.0	16.84	0.0	0.0
Seq2Seq$_{ST}$	17.4	10.11	19.0	15.8	11.0	10.83	13.3	8.8
Seq2Seq$_{MT}$	18.1	9.69	20.3	16.0	11.8	10.76	14.1	9.3
Chen *et al.* [6]	20.1	8.84	21.5	17.1	13.1	9.26	15.7	10.4
VIENNA$_{ST}$	22.4	8.76	22.4	17.3	14.3	9.22	16.5	10.6
VIENNA$_{MT}$	**25.3**	**8.61**	**23.9**	**17.8**	**18.7**	**8.93**	**17.9**	**12.5**

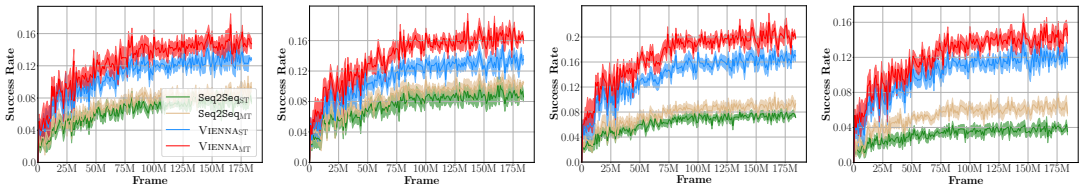
(b) *audio-goal nav.* (AGN)

Models	val seen				val unseen			
	SR↑	NE↓	OR↑	SPL↑	**SR**↑	NE↓	OR↑	SPL↑
Random	0.8	7.67	1.0	0.8	2.0	7.56	2.1	1.7
Seq2Seq$_{ST}$	26.7	6.61	33.3	14.4	8.9	7.31	11.1	4.4
Seq2Seq$_{MT}$	28.7	6.45	35.0	15.8	10.8	7.13	14.0	4.8
Chaplot *et al.* [2]	31.3	6.15	35.2	16.7	17.6	7.08	21.3	7.5
VIENNA$_{ST}$	33.2	6.11	36.4	17.1	18.5	6.95	22.1	8.1
VIENNA$_{MT}$	**33.3**	**5.92**	**37.8**	**17.7**	**19.4**	**6.77**	**25.1**	**10.7**

(c) *object-goal nav.* (OGN)

Models	val seen				val unseen			
	SR↑	NE↓	OR↑	SPL↑	**SR**↑	NE↓	OR↑	SPL↑
Random	0.0	8.89	0.0	0.0	0.0	8.92	0.0	0.0
Seq2Seq$_{ST}$	13.2	7.54	17.7	12.1	5.2	8.49	9.7	4.6
Seq2Seq$_{MT}$	17.6	7.29	22.8	15.4	7.6	8.21	13.4	6.5
Krantz *et al.* [25]	23.7	7.22	25.9	21.2	11.0	7.60	16.2	10.2
VIENNA$_{ST}$	23.9	7.16	26.1	22.2	14.3	7.35	18.5	12.5
VIENNA$_{MT}$	**26.5**	**7.08**	**27.9**	**24.1**	**16.3**	**7.26**	**20.6**	**15.7**

(d) *vision-language nav.* (VLN)



(a) *image-goal nav.* (b) *audio-goal nav.* (c) *object-goal nav.* (d) *vision-language nav.*

Figure 4: Training curves of VIENNA agents compared to Seq2Seq agents on the four VXN tasks (§5.1).

Metric. Four widely-used metrics are adopted for evaluation: i) *Success Rate* (**SR**); ii) *Navigation Error* (NE); iii) *Oracle success Rate* (OR); and iv) *Success rate weighted by Path Length* (SPL) [114].

5.1 Performance Benchmarking

Table 3 reports the comparison results on the four VXN tasks. Some key conclusions are list below:

- VIENNA obtains impressive results, under val seen and unseen sets, across all the tasks and evaluation metrics. This proves the versatility of VIENNA and the power of our parse-and-query regime.
- VIENNA consistently outperforms Seq2Seq, no matter they are trained on single tasks individually or multiple tasks jointly. Compared with other task-specific competitors [2,5,6,25], VIENNA gains comparable results on *audio-goal nav.* and *object-goal nav.*, and performs better on *image-goal nav.* and *vision-language nav.* tasks. These results verify the effectiveness of our model design.
- When considering the performance gain from the single-task setting to multitask, VIENNA yields more promising results, compared with Seq2Seq. For example, in Table 3a, VIENNA$_{MT}$ outperforms VIENNA$_{ST}$ by 2.2% SR and 1.7% SR, on val seen and unseen, respectively; however, in the same condition, Seq2Seq$_{MT}$ only provides 0.7% and 0.9% SR gains over Seq2Seq$_{ST}$. These results demonstrates that VIENNA can make a better use of cross-task knowledge.
- When considering the performance gap between seen and unseen environments, VIENNA$_{MT}$ is more favored than its single-task counterpart, VIENNA$_{ST}$. For instance, in Table 3c, VIENNA$_{ST}$ suffers from relatively large performance drop, *i.e.*, 33.2%→18.5% SR; however, VIENNA$_{MT}$ shows reduced degradation, *i.e.*, 33.3%→19.4% SR, in unseen environments. This indicates that investigating inter-task relatedness may help to strengthen the generalizability of navigation agents.
- The above results are particularly impressive considering the advantage of VIENNA in efficient parameter utilization, *i.e.*, VIENNA$_{MT}$ (31 M) *vs* VIENNA$_{ST}$× 4 (101 M) *vs* Seq2Seq$_{MT}$ (27 M) *vs* Seq2Seq$_{ST}$× 4 (93 M) *vs* [5] + [6] + [2] + [25] (165M = 40 M + 45 M + 38 M + 42 M).

Fig. 4 plots the training curves of VIENNA$_{ST/MT}$ compared to Seq2Seq$_{ST/MT}$ for the four VXN tasks in unseen envs. Aligning with the results in Table 3, VIENNA outperforms Seq2Seq, and benefits more from multiple task learning. This shows that VIENNA makes a better use of cross-task knowledge.

Table 4: Ablation studies (§5.2) with *audio-goal nav.* (AGN) and *vision-language nav.* (VLN) tasks.

Modality (§4.2)	AGN (**SR**$^\uparrow$) seen/unseen	VLN (**SR**$^\uparrow$) seen/unseen
RGB *only*	2.5 / 2.1	21.1 / 11.2
audio *only*	23.1 / 15.9	0.3 / 0.2
RGBD *only*	2.4 / 2.3	21.9 / 12.5
RGBD+audio	25.3 / 18.7	26.5 / 16.3

(a) multisensory integration

$\boldsymbol{G}$ (Eq. 7)	AGN (**SR**$^\uparrow$) seen/unseen	VLN (**SR**$^\uparrow$) seen/unseen
episodic target only	23.1 / 17.2	22.7 / 14.1
episodic target + episodic task embedding	24.2 / 17.9	25.1 / 15.5
augmented target des. embed.	25.3 / 18.7	26.5 / 16.3

(b) augmented target description embedding

$\boldsymbol{Q}_t$ (Eq. 8)	AGN (**SR**$^\uparrow$) seen/unseen	VLN (**SR**$^\uparrow$) seen/unseen
$N=1$	21.0 / 15.6	22.2 / 13.2
$N=3$	23.8 / 17.8	25.7 / 15.5
$N=5$	25.3 / 18.7	26.5 / 16.3
$N=7$	24.9 / 18.3	26.2 / 16.2

(c) diversified target parsing

F_{MTP} (Eq. 9)	AGN (**SR**$^\uparrow$) seen/unseen	VLN (**SR**$^\uparrow$) seen/unseen
separate	23.2 / 17.4	25.0 / 15.1
1-shared	24.4 / 18.1	25.8 / 15.7
2-shared	25.3 / 18.7	26.5 / 16.3
3-shared	24.8 / 17.9	25.9 / 15.5
all-shared	24.1 / 17.6	25.6 / 15.3

(d) multitask planner

R (§4.4)	AGN (**SR**$^\uparrow$) seen/unseen	VLN (**SR**$^\uparrow$) seen/unseen
r_{success}	2.1 / 1.5	5.5 / 2.3
$r_{\text{success}}+r_{\text{progress}}$	22.5 / 16.3	23.8 / 14.7
$r_{\text{success}}+r_{\text{progress}}+r_{\text{slack}}$	23.1 / 16.9	24.3 / 15.1
$r_{\text{success}}+r_{\text{slack}}+r_{\text{progress}}+r_{\text{explore}}$	25.3 / 18.7	26.5 / 16.3

(e) reward function

Task	AGN (**SR**$^\uparrow$) seen/unseen	VLN (**SR**$^\uparrow$) seen/unseen
single task	22.1 / 15.4	23.8 / 14.1
AGN + VLN	22.7 / 16.1	24.4 / 14.9
AGN + VLN + IGN	24.1 / 17.3	25.1 / 15.5
AGN + VLN + IGN + OGN	25.3 / 18.7	26.5 / 16.3

(f) multitask learning

5.2 Ablative Study

To thoroughly test the efficacy of crucial components of VIENNA, we conduct a series of diagnostic studies on *vision-language nav.* and *audio-goal nav.* tasks. The results are summarized in Table 4.

Multisensory Integration. Agents in VXN are equipped with a multimodal sensor so as to find the target by both seeing and hearing and make our navigation setting closer the real-world. We first study the influence of different sensory signals (*i.e.*, RGB, depth, audio) by training VIENNA with varying sensory modalities. As shown in Table 4a, fusing multimodal sensory cues (*i.e.*, RGBD + audio) is more favored. For example, in VLN, although considering audio alone brings poor performance, supplementing RGBD perception with audio yields notable improvements. This suggests audio is complementary to visual sensory in capturing physical and semantic properties of environments.

Augmented Target Description Embedding. To better master cross-task knowledge, VIENNA augments its episodic targets with all the four learnable task embeddings $\boldsymbol{\tau}_{I,A,T,L}$ (*cf.* Eq. 7). We compare this design against two variants in Table 4b, and find such a strategy is conducive to the performance. This is because, through end-to-end training, $\boldsymbol{\tau}_{I,A,T,L}$ carry task-specific knowledge, *e.g.*, $\boldsymbol{\tau}_A$ is associated with some discriminative audio clips; $\boldsymbol{\tau}_I$ focuses on essential visual landmarks. By taking $\boldsymbol{\tau}_{I,A,T,L}$ together, VIENNA use key knowledge of different tasks in single task episodes.

Diversified Target Parsing. We online parse the augmented target description embedding $\boldsymbol{G}$ into N target embeddings $\boldsymbol{Q}_t = [\boldsymbol{q}_t^1, \cdots, \boldsymbol{q}_t^N]$ (*cf.* Eq. 8), to achieve vivid and diversified interpretations of $\boldsymbol{G}$. In Table 4c, we present evaluation scores with different numbers of generated target embeddings, *i.e.*, $N = 1, 3, 5, 7$. As can be seen, diversified target parsing indeed boots navigation performance.

Multitask Planner. Several variants of multitask planner f_{MTP} (*cf.* Eq. 9) are compared in Table 4d. The two-layer shared trunk design is adopted, due to its relatively better performance.

Reward Function. Next we examine the design of our reward function (§4.4). As seen in Table 4e, each reward term is indeed useful and combining all the four terms leads to the best performance.

Multitask Learning. Table 4f reveals the value of training VIENNA on multiple tasks: training with more navigation tasks improves both performance and generalizability. Compared to a composition of four single-task models, multi-task VIENNA also greatly reduces the model size: 101M$\rightarrow$31M.

6 Conclusion

In this work, we present VXN, a large-scale 3D indoor dataset for multimodal, multitask navigation in continuous and audiovisual complex environments. Further, we devise VIENNA, a powerful agent that simultaneously learns four famous navigation tasks within a single unified parsing-and-query scheme. We empirically show that, through a fully attentive architecture, VIENNA is able to mine and utilize cross-task knowledge to enhance the performance on all the tasks. These efforts move us closer to a community goal of general-purpose robots capable of fulfilling a multitude of tasks.

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References

[1] Dongsung Kim and Ramakant Nevatia. Symbolic navigation with a generic map. *Autonomous Robots*, 6(1):69–88, 1999. 1

[2] Devendra Singh Chaplot, Dhiraj Gandhi, Abhinav Gupta, and Ruslan Salakhutdinov. Object goal navigation using goal-oriented semantic exploration. In *NeurIPS*, 2020. 1, 8, 9, 16

[3] Devendra Singh Chaplot, Ruslan Salakhutdinov, Abhinav Gupta, and Saurabh Gupta. Neural topological SLAM for visual navigation. In *CVPR*, 2020. 1, 3, 4, 5

[4] Kristina Striegnitz, Alexandre Denis, Andrew Gargett, Konstantina Garoufi, Alexander Koller, and Mariët Theune. Report on the second challenge on generating instructions in virtual environments (give-2.5). In *European Workshop on Natural Language Generation*, 2011. 1

[5] Yuke Zhu, Roozbeh Mottaghi, Eric Kolve, Joseph J Lim, Abhinav Gupta, Li Fei-Fei, and Ali Farhadi. Target-driven visual navigation in indoor scenes using deep reinforcement learning. In *ICRA*, 2017. 1, 3, 4, 8, 9

[6] Changan Chen, Unnat Jain, Carl Schissler, Sebastia Vicenc Amengual Gari, Ziad Al-Halah, Vamsi Krishna Ithapu, Philip Robinson, and Kristen Grauman. Soundspaces: Audio-visual navigation in 3d environments. In *ECCV*, 2020. 1, 3, 4, 5, 8, 9, 16

[7] Wei Yang, Xiaolong Wang, Ali Farhadi, Abhinav Gupta, and Roozbeh Mottaghi. Visual semantic navigation using scene priors. In *ICLR*, 2019. 1, 3, 4

[8] Peter Anderson, Qi Wu, Damien Teney, Jake Bruce, Mark Johnson, Niko Sünderhauf, Ian Reid, Stephen Gould, and Anton van den Hengel. Vision-and-language navigation: Interpreting visually-grounded navigation instructions in real environments. In *CVPR*, 2018. 1, 3, 4, 5, 8

[9] Yu Zhang and Qiang Yang. An overview of multi-task learning. *National Science Review*, 5(1):30–43, 2018. 2

[10] M Alex Meredith and Barry E Stein. Visual, auditory, and somatosensory convergence on cells in superior colliculus results in multisensory integration. *Journal of neurophysiology*, 56(3):640–662, 1986. 2

[11] Konrad P Körding, Ulrik Beierholm, Wei Ji Ma, Steven Quartz, Joshua B Tenenbaum, and Ladan Shams. Causal inference in multisensory perception. *PLoS one*, 2(9):e943, 2007. 2

[12] Rich Caruana. Multitask learning. *Machine learning*, 28(1):41–75, 1997. 2, 3

[13] Michael Crawshaw. Multi-task learning with deep neural networks: A survey. *arXiv preprint arXiv:2009.09796*, 2020. 2, 3

[14] Yu Zhang and Qiang Yang. A survey on multi-task learning. *TKDE*, 2021. 2

[15] Manolis Savva, Abhishek Kadian, Oleksandr Maksymets, Yili Zhao, Erik Wijmans, Bhavana Jain, Julian Straub, Jia Liu, Vladlen Koltun, Jitendra Malik, et al. Habitat: A platform for embodied ai research. In *ICCV*, 2019. 2, 3, 4, 5, 16

[16] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Lukasz Kaiser, and Illia Polosukhin. Attention is all you need. In *NeurIPS*, 2017. 2, 3, 5, 8

[17] Georges Giralt, Ralph Sobek, and Raja Chatila. A multi-level planning and navigation system for a mobile robot: a first approach to hilare. In *IJCAI*, 1979. 2

[18] Iro Armeni, Ozan Sener, Amir R Zamir, Helen Jiang, Ioannis Brilakis, Martin Fischer, and Silvio Savarese. 3D semantic parsing of large-scale indoor spaces. In *CVPR*, 2016. 2

[19] Angel Chang, Angela Dai, Thomas Funkhouser, Maciej Halber, Matthias Niebner, Manolis Savva, Shuran Song, Andy Zeng, and Yinda Zhang. Matterport3D: Learning from rgb-d data in indoor environments. In *3DV*, 2018. 2, 4, 16

[20] Yi Wu, Yuxin Wu, Georgia Gkioxari, and Yuandong Tian. Building generalizable agents with a realistic and rich 3d environment. *arXiv preprint arXiv:1801.02209*, 2018. 2

[21] Shuran Song, Fisher Yu, Andy Zeng, Angel X Chang, Manolis Savva, and Thomas Funkhouser. Semantic scene completion from a single depth image. In *CVPR*, 2017. 2

[22] Eric Kolve, Roozbeh Mottaghi, Winson Han, Eli VanderBilt, Luca Weihs, Alvaro Herrasti, Daniel Gordon, Yuke Zhu, Abhinav Gupta, and Ali Farhadi. Ai2-thor: An interactive 3d environment for visual ai. *arXiv preprint arXiv:1712.05474*, 2017. 3, 4

[23] Fei Xia, Amir R Zamir, Zhiyang He, Alexander Sax, Jitendra Malik, and Silvio Savarese. Gibson env: Real-world perception for embodied agents. In *CVPR*, 2018. 3

[24] Matt Deitke, Winson Han, Alvaro Herrasti, Aniruddha Kembhavi, Eric Kolve, Roozbeh Mottaghi, Jordi Salvador, Dustin Schwenk, Eli VanderBilt, Matthew Wallingford, et al. Robothor: An open simulation-to-real embodied ai platform. In *CVPR*, 2020. 3

[25] Jacob Krantz, Erik Wijmans, Arjun Majumdar, Dhruv Batra, and Stefan Lee. Beyond the nav-graph: Vision-and-language navigation in continuous environments. In *ECCV*, 2020. 3, 4, 8, 9, 16

[26] Abhishek Das, Samyak Datta, Georgia Gkioxari, Stefan Lee, Devi Parikh, and Dhruv Batra. Embodied question answering. In *CVPR*, 2018. 3, 4

[27] Jesse Thomason, Michael Murray, Maya Cakmak, and Luke Zettlemoyer. Vision-and-dialog navigation. In *CoRL*, 2019. 3

[28] Khanh Nguyen, Debadeepta Dey, Chris Brockett, and Bill Dolan. Vision-based navigation with language-based assistance via imitation learning with indirect intervention. In *CVPR*, 2018. 3

[29] Khanh Nguyen and Hal Daumé III. Help, anna! visual navigation with natural multimodal assistance via retrospective curiosity-encouraging imitation learning. In *EMNLP-IJCNLP*, 2019. 3

[30] Haiyang Wang, Wenguan Wang, Xizhou Zhu, Jifeng Dai, and Liwei Wang. Collaborative visual navigation. *arXiv preprint arXiv:2107.01151*, 2021. 3

[31] Piotr Mirowski, Razvan Pascanu, Fabio Viola, Hubert Soyer, Andrew J Ballard, Andrea Banino, Misha Denil, Ross Goroshin, Laurent Sifre, Koray Kavukcuoglu, et al. Learning to navigate in complex environments. In *ICLR*, 2017. 3

[32] Saurabh Gupta, James Davidson, Sergey Levine, Rahul Sukthankar, and Jitendra Malik. Cognitive mapping and planning for visual navigation. In *CVPR*, 2017. 3

[33] Emilio Parisotto and Ruslan Salakhutdinov. Neural map: Structured memory for deep reinforcement learning. In *ICLR*, 2019. 3

[34] Jingwei Zhang, Lei Tai, Joschka Boedecker, Wolfram Burgard, and Ming Liu. Neural slam: Learning to explore with external memory. *arXiv preprint arXiv:1706.09520*, 2017. 3

[35] Yi Wu, Yuxin Wu, Aviv Tamar, Stuart Russell, Georgia Gkioxari, and Yuandong Tian. Bayesian relational memory for semantic visual navigation. In *ICCV*, 2019. 3

[36] Devendra Singh Chaplot, Emilio Parisotto, and Ruslan Salakhutdinov. Active neural localization. In *ICLR*, 2018. 3

[37] Nikolay Savinov, Alexey Dosovitskiy, and Vladlen Koltun. Semi-parametric topological memory for navigation. In *ICLR*, 2018. 3

[38] Devendra Singh Chaplot, Dhiraj Gandhi, Saurabh Gupta, Abhinav Gupta, and Ruslan Salakhutdinov. Learning to explore using active neural slam. In *ICLR*, 2020. 3

[39] Hanqing Wang, Wenguan Wang, Wei Liang, Caiming Xiong, and Jianbing Shen. Structured scene memory for vision-language navigation. In *CVPR*, 2021. 3

[40] Kevin Chen, Junshen K. Chen, Jo Chuang, Marynel Vazquez, and Silvio Savarese. Topological planning with transformers for vision-and-language navigation. In *CVPR*, 2021. 3

[41] Yusheng Zhao, Jinyu Chen, Chen Gao, Wenguan Wang, Lirong Yang, Haibing Ren, Huaxia Xia, and Si Liu. Target-driven structured transformer planner for vision-language navigation. In *ACMMM*, 2022. 3

[42] Lisa Lee, Emilio Parisotto, Devendra Singh Chaplot, Eric Xing, and Ruslan Salakhutdinov. Gated path planning networks. In *ICML*, 2018. 3

[43] Zhiwei Deng, Karthik Narasimhan, and Olga Russakovsky. Evolving graphical planner: Contextual global planning for vision-and-language navigation. *arXiv preprint arXiv:2007.05655*, 2020. 3, 5

[44] Hanqing Wang, Wenguan Wang, Tianmin Shu, Wei Liang, and Jianbing Shen. Active visual information gathering for vision-language navigation. In *ECCV*, 2020. 3

[45] Ronghang Hu, Daniel Fried, Anna Rohrbach, Dan Klein, Trevor Darrell, and Kate Saenko. Are you looking? grounding to multiple modalities in vision-and-language navigation. In *ACL*, 2019. 3

[46] Yuankai Qi, Zizheng Pan, Shengping Zhang, Anton van den Hengel, and Qi Wu. Object-and-action aware model for visual language navigation. In *ECCV*, 2020. 3

[47] Xin Eric Wang, Vihan Jain, Eugene Ie, William Yang Wang, Zornitsa Kozareva, and Sujith Ravi. Environment-agnostic multitask learning for natural language grounded navigation. In *ECCV*, 2020. 3

[48] Yicong Hong, Qi Wu, Yuankai Qi, Cristian Rodriguez-Opazo, and Stephen Gould. Vln bert: A recurrent vision-and-language bert for navigation. In *CVPR*, 2021. 3

[49] Daniel Fried, Ronghang Hu, Volkan Cirik, Anna Rohrbach, Jacob Andreas, Louis-Philippe Morency, Taylor Berg-Kirkpatrick, Kate Saenko, Dan Klein, and Trevor Darrell. Speaker-follower models for vision-and-language navigation. In *NeurIPS*, 2018. 3

[50] Hao Tan, Licheng Yu, and Mohit Bansal. Learning to navigate unseen environments: Back translation with environmental dropout. In *NAACL*, 2019. 3

[51] Tsu-Jui Fu, Xin Wang, Matthew Peterson, Scott Grafton, Miguel Eckstein, and William Yang Wang. Counterfactual vision-and-language navigation via adversarial path sampling. In *ECCV*, 2020. 3

[52] Arjun Majumdar, Ayush Shrivastava, Stefan Lee, Peter Anderson, Devi Parikh, and Dhruv Batra. Improving vision-and-language navigation with image-text pairs from the web. In *ECCV*, 2020. 3, 4

[53] Weituo Hao, Chunyuan Li, Xiujun Li, Lawrence Carin, and Jianfeng Gao. Towards learning a generic agent for vision-and-language navigation via pre-training. In *CVPR*, 2020. 3

[54] Hanqing Wang, Wei Liang, Jianbing Shen, Luc Van Gool, and Wenguan Wang. Counterfactual cycle-consistent learning for instruction following and generation in vision-language navigation. In *CVPR*, 2022. 3

[55] Chen Gao, Jinyu Chen, Si Liu, Luting Wang, Qiong Zhang, and Qi Wu. Room-and-object aware knowledge reasoning for remote embodied referring expression. In *CVPR*, 2021. 3

[56] Sebastian Ruder. An overview of multi-task learning in deep neural networks. *arXiv preprint arXiv:1706.05098*, 2017. 3

[57] Wenguan Wang, Yuanlu Xu, Jianbing Shen, and Song-Chun Zhu. Attentive fashion grammar network for fashion landmark detection and clothing category classification. In *CVPR*, 2018. 3

[58] Wenguan Wang, Shuyang Zhao, Jianbing Shen, Steven CH Hoi, and Ali Borji. Salient object detection with pyramid attention and salient edges. In *CVPR*, 2019. 3

[59] Jiasen Lu, Vedanuj Goswami, Marcus Rohrbach, Devi Parikh, and Stefan Lee. 12-in-1: Multi-task vision and language representation learning. In *CVPR*, 2020. 3

[60] Ronan Collobert and Jason Weston. A unified architecture for natural language processing: Deep neural networks with multitask learning. In *ICML*, 2008. 3

[61] Zhanpeng Zhang, Ping Luo, Chen Change Loy, and Xiaoou Tang. Facial landmark detection by deep multi-task learning. In *ECCV*, 2014. 3

[62] Ishan Misra, Abhinav Shrivastava, Abhinav Gupta, and Martial Hebert. Cross-stitch networks for multi-task learning. In *CVPR*, 2016. 3

[63] Dan Xu, Wanli Ouyang, Xiaogang Wang, and Nicu Sebe. Pad-net: Multi-tasks guided prediction-and-distillation network for simultaneous depth estimation and scene parsing. In *CVPR*, 2018. 3

[64] Gjorgji Strezoski, Nanne van Noord, and Marcel Worring. Many task learning with task routing. In *ICCV*, 2019. 3

[65] Alex Kendall, Yarin Gal, and Roberto Cipolla. Multi-task learning using uncertainty to weigh losses for scene geometry and semantics. In *CVPR*, 2018. 3

[66] Zhao Chen, Vijay Badrinarayanan, Chen-Yu Lee, and Andrew Rabinovich. Gradnorm: Gradient normalization for adaptive loss balancing in deep multitask networks. In *ICML*, 2018. 3

[67] Michelle Guo, Albert Haque, De-An Huang, Serena Yeung, and Li Fei-Fei. Dynamic task prioritization for multitask learning. In *ECCV*, 2018. 3

[68] Long Duong, Trevor Cohn, Steven Bird, and Paul Cook. Low resource dependency parsing: Cross-lingual parameter sharing in a neural network parser. In *IJCNLP*, 2015. 3

[69] Victor Sanh, Thomas Wolf, and Sebastian Ruder. A hierarchical multi-task approach for learning embeddings from semantic tasks. In *AAAI*, 2019. 3

[70] Ozan Sener and Vladlen Koltun. Multi-task learning as multi-objective optimization. In *NeurIPS*, 2018. 3

[71] Joachim Bingel and Anders Søgaard. Identifying beneficial task relations for multi-task learning in deep neural networks. In *ACL*, 2017. 3

[72] Amir R Zamir, Alexander Sax, William Shen, Leonidas J Guibas, Jitendra Malik, and Silvio Savarese. Taskonomy: Disentangling task transfer learning. In *CVPR*, 2018. 3

[73] Kshitij Dwivedi and Gemma Roig. Representation similarity analysis for efficient task taxonomy & transfer learning. In *CVPR*, 2019. 3

[74] Zhaoyang Yang, Kathryn E Merrick, Hussein A Abbass, and Lianwen Jin. Multi-task deep reinforcement learning for continuous action control. In *IJCAI*, 2017. 3

[75] Yee Whye Teh, Victor Bapst, Wojciech Marian Czarnecki, John Quan, James Kirkpatrick, Raia Hadsell, Nicolas Heess, and Razvan Pascanu. Distral: robust multitask reinforcement learning. In *NeurIPS*, 2017. 3

[76] Lasse Espeholt, Hubert Soyer, Remi Munos, Karen Simonyan, Vlad Mnih, Tom Ward, Yotam Doron, Vlad Firoiu, Tim Harley, Iain Dunning, et al. Impala: Scalable distributed deep-rl with importance weighted actor-learner architectures. In *ICML*, 2018. 3

[77] Lerrel Pinto and Abhinav Gupta. Learning to push by grasping: Using multiple tasks for effective learning. In *ICRA*, 2017. 3

[78] Andy Zeng, Shuran Song, Stefan Welker, Johnny Lee, Alberto Rodriguez, and Thomas Funkhouser. Learning synergies between pushing and grasping with self-supervised deep reinforcement learning. In *IROS*, 2018. 3

[79] Matteo Hessel, Hubert Soyer, Lasse Espeholt, Wojciech Czarnecki, Simon Schmitt, and Hado van Hasselt. Multi-task deep reinforcement learning with popart. In *AAAI*, 2019. 3

[80] Carlo D'Eramo, Davide Tateo, Andrea Bonarini, Marcello Restelli, and Jan Peters. Sharing knowledge in multi-task deep reinforcement learning. In *ICLR*, 2020. 3

[81] Zhiyuan Xu, Kun Wu, Zhengping Che, Jian Tang, and Jieping Ye. Knowledge transfer in multi-task deep reinforcement learning for continuous control. *arXiv preprint arXiv:2010.07494*, 2020. 3

[82] Nicolas Heess, Greg Wayne, Yuval Tassa, Timothy Lillicrap, Martin Riedmiller, and David Silver. Learning and transfer of modulated locomotor controllers. *arXiv preprint arXiv:1610.05182*, 2016. 3

[83] Coline Devin, Abhishek Gupta, Trevor Darrell, Pieter Abbeel, and Sergey Levine. Learning modular neural network policies for multi-task and multi-robot transfer. In *ICRA*, 2017. 3

[84] Andrei A Rusu, Sergio Gomez Colmenarejo, Caglar Gulcehre, Guillaume Desjardins, James Kirkpatrick, Razvan Pascanu, Volodymyr Mnih, Koray Kavukcuoglu, and Raia Hadsell. Policy distillation. In *ICLR*, 2015. 3

[85] Emilio Parisotto, Lei Jimmy Ba, and Ruslan Salakhutdinov. Actor-mimic: Deep multitask and transfer reinforcement learning. In *ICLR*, 2016. 3

[86] Charles Beattie, Joel Z Leibo, Denis Teplyashin, Tom Ward, Marcus Wainwright, Heinrich Küttler, Andrew Lefrancq, Simon Green, Víctor Valdés, Amir Sadik, et al. Deepmind lab. *arXiv preprint arXiv:1612.03801*, 2016. 3

[87] Marc G Bellemare, Yavar Naddaf, Joel Veness, and Michael Bowling. The arcade learning environment: An evaluation platform for general agents. *Journal of Artificial Intelligence Research*, 47:253–279, 2013. 3

[88] Tianhe Yu, Deirdre Quillen, Zhanpeng He, Ryan Julian, Karol Hausman, Chelsea Finn, and Sergey Levine. Meta-world: A benchmark and evaluation for multi-task and meta reinforcement learning. In *Conference on Robot Learning*, 2020. 3

[89] Devendra Singh Chaplot, Lisa Lee, Ruslan Salakhutdinov, Devi Parikh, and Dhruv Batra. Embodied multimodal multitask learning. *arXiv preprint arXiv:1902.01385*, 2019. 3

[90] Piotr Mirowski, Razvan Pascanu, Fabio Viola, Hubert Soyer, Andrew J Ballard, Andrea Banino, Misha Denil, Ross Goroshin, Laurent Sifre, Koray Kavukcuoglu, et al. Learning to navigate in complex environments. In *ICLR*, 2017. 3

[91] Daniel Gordon, Abhishek Kadian, Devi Parikh, Judy Hoffman, and Dhruv Batra. Splitnet: Sim2sim and task2task transfer for embodied visual navigation. In *ICCV*, 2019. 3, 4, 5

[92] Deepak Pathak, Pulkit Agrawal, Alexei A Efros, and Trevor Darrell. Curiosity-driven exploration by self-supervised prediction. In *ICML*, 2017. 3

[93] Karol Gregor, Danilo Jimenez Rezende, Frederic Besse, Yan Wu, Hamza Merzic, and Aaron van den Oord. Shaping belief states with generative environment models for rl. In *NeurIPS*, 2019. 3

[94] Joel Ye, Dhruv Batra, Erik Wijmans, and Abhishek Das. Auxiliary tasks speed up learning pointgoal navigation. *arXiv preprint arXiv:2007.04561*, 2020. 3

[95] Chih-Yao Ma, Jiasen Lu, Zuxuan Wu, Ghassan AlRegib, Zsolt Kira, Richard Socher, and Caiming Xiong. Self-monitoring navigation agent via auxiliary progress estimation. In *ICLR*, 2019. 3

[96] Fengda Zhu, Yi Zhu, Xiaojun Chang, and Xiaodan Liang. Vision-language navigation with self-supervised auxiliary reasoning tasks. In *CVPR*, 2020. 3

[97] Kuan Fang, Alexander Toshev, Li Fei-Fei, and Silvio Savarese. Scene memory transformer for embodied agents in long-horizon tasks. In *CVPR*, 2019. 3

[98] Federico Landi, Lorenzo Baraldi, Marcella Cornia, Massimiliano Corsini, and Rita Cucchiara. Perceive, transform, and act: Multi-modal attention networks for vision-and-language navigation. *arXiv preprint arXiv:1911.12377*, 2020. 3

[99] Changan Chen, Ziad Al-Halah, and Kristen Grauman. Semantic audio-visual navigation. In *CVPR*, 2021. 3, 4, 5

[100] Heming Du, Xin Yu, and Liang Zheng. Vtnet: Visual transformer network for object goal navigation. *arXiv preprint arXiv:2105.09447*, 2021. 3

[101] Alexander Pashevich, Cordelia Schmid, and Chen Sun. Episodic transformer for vision-and-language navigation. *arXiv preprint arXiv:2105.06453*, 2021. 3

[102] Lukasz Kaiser, Aidan N Gomez, Noam Shazeer, Ashish Vaswani, Niki Parmar, Llion Jones, and Jakob Uszkoreit. One model to learn them all. *arXiv preprint arXiv:1706.05137*, 2017. 3

[103] Jiasen Lu, Dhruv Batra, Devi Parikh, and Stefan Lee. Vilbert: Pretraining task-agnostic visiolinguistic representations for vision-and-language tasks. *arXiv preprint arXiv:1908.02265*, 2019. 3

[104] Subhojeet Pramanik, Priyanka Agrawal, and Aman Hussain. Omninet: A unified architecture for multi-modal multi-task learning. *arXiv preprint arXiv:1907.07804*, 2019. 3

[105] Ronghang Hu and Amanpreet Singh. Unit: Multimodal multitask learning with a unified transformer. *arXiv preprint arXiv:2102.10772*, 2021. 3

[106] Weituo Hao, Chunyuan Li, Xiujun Li, Lawrence Carin, and Jianfeng Gao. Towards learning a generic agent for vision-and-language navigation via pre-training. In *CVPR*, 2020. 4

[107] Juncheng Li, Xin Wang, Siliang Tang, Haizhou Shi, Fei Wu, Yueting Zhuang, and William Yang Wang. Unsupervised reinforcement learning of transferable meta-skills for embodied navigation. In *CVPR*, 2020. 4

[108] Pierre-Louis Guhur, Makarand Tapaswi, Shizhe Chen, Ivan Laptev, and Cordelia Schmid. Airbert: In-domain Pretraining for Vision-and-Language Navigation. In *ICCV*, 2021. 4

[109] Dhruv Batra, Aaron Gokaslan, Aniruddha Kembhavi, Oleksandr Maksymets, Roozbeh Mottaghi, Manolis Savva, Alexander Toshev, and Erik Wijmans. ObjectNav Revisited: On Evaluation of Embodied Agents Navigating to Objects. *arXiv preprint arXiv:2006.13171*, 2020. 4, 5

[110] Habitat image nav repository. `https://github.com/facebookresearch/habitat-lab/pull/333`. 4

[111] Z. Markus, S. Christian, and H. Robert. Binaural rendering of ambisonic signals by head-related impulse response time alignment and a diffuseness constraint. *The Journal of the Acoustical Society of America*, 143(6):3616–3627, 2018. 4

[112] Gavin Kearney, Claire Masterson, Stephen Adams, and Frank Boland. Approximation of binaural room impulse responses. In *ISSC*, 2009. 4

[113] Hiroaki Sakoe and Seibi Chiba. Dynamic programming algorithm optimization for spoken word recognition. *IEEE Transactions on Acoustics, Speech, and Signal processing*, 26(1):43–49, 1978. 4

[114] Peter Anderson, Angel Chang, Devendra Singh Chaplot, Alexey Dosovitskiy, Saurabh Gupta, Vladlen Koltun, Jana Kosecka, Jitendra Malik, Roozbeh Mottaghi, Manolis Savva, et al. On evaluation of embodied navigation agents. *arXiv preprint arXiv:1807.06757*, 2018. 5, 9

[115] Howard Chen, Alane Suhr, Dipendra Misra, Noah Snavely, and Yoav Artzi. Touchdown: Natural language navigation and spatial reasoning in visual street environments. In *CVPR*, 2019. 5

[116] Richard Bellman. A markovian decision process. *Journal of mathematics and mechanics*, 6(5):679–684, 1957. 5

[117] Nicolas Heess, Dhruva TB, Srinivasan Sriram, Jay Lemmon, Josh Merel, Greg Wayne, Yuval Tassa, Tom Erez, Ziyu Wang, SM Eslami, et al. Emergence of locomotion behaviours in rich environments. *arXiv preprint arXiv:1707.02286*, 2017. 5, 8

[118] Joel Ye, Dhruv Batra, Abhishek Das, and Erik Wijmans. Auxiliary tasks and exploration enable objectnav. *arXiv preprint arXiv:2104.04112*, 2021. 8

[119] John Schulman, Filip Wolski, Prafulla Dhariwal, Alec Radford, and Oleg Klimov. Proximal policy optimization algorithms. *arXiv preprint arXiv:1707.06347*, 2017. 8

[120] Olga Russakovsky, Jia Deng, Hao Su, Jonathan Krause, Sanjeev Satheesh, Sean Ma, Zhiheng Huang, Andrej Karpathy, Aditya Khosla, Michael Bernstein, Alexander C. Berg, and Li Fei-Fei. ImageNet Large Scale Visual Recognition Challenge. *IJCV*, 115(3):211–252, 2015. 8

[121] Kaiming He, Xiangyu Zhang, Shaoqing Ren, and Jian Sun. Deep residual learning for image recognition. In *CVPR*, 2016. 8

[122] Ilya Loshchilov and Frank Hutter. Fixing weight decay regularization in adam. In *ICLR*, 2018. 8

Checklist

1. For all authors...
   (a) Do the main claims made in the abstract and introduction accurately reflect the paper's contributions and scope? [Yes] Our main claims accurately reflect the paper's contributions and scope.

(b) Did you describe the limitations of your work? [Yes] The limitations are discussed in the supplemental material.

(c) Did you discuss any potential negative societal impacts of your work? [Yes] The potential negative societal impacts are discussed in the supplemental material.

(d) Have you read the ethics review guidelines and ensured that your paper conforms to them? [Yes] We have already read the ethics review guidelines and ensured that our paper conforms to them.

2. If you are including theoretical results...

(a) Did you state the full set of assumptions of all theoretical results? [N/A] Our work does not involve any theoretical result.

(b) Did you include complete proofs of all theoretical results? [N/A] Our work does not involve any theoretical result.

3. If you ran experiments...

(a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? [Yes] The code and full dataset is available on the project page: https://github.com/hanqingwangai/VXN.

(b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? [Yes] We specify all the training details in §4.5 and §I of supplementary.

(c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? [Yes] We report the error bars in Fig. 4.

(d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? [Yes] We report our compute hardware in §4.5.

4. If you are using existing assets (e.g., code, data, models) or curating/releasing new assets...

(a) If your work uses existing assets, did you cite the creators? [Yes] We have cited all the used code and data.

(b) Did you mention the license of the assets? [Yes] Habitat Simulator [15] is obtained (https://github.com/facebookresearch/habitat-lab) with MIT license. The algorithm of Chen *et al*. [6] is implemented based on the publicly released code (https://github.com/facebookresearch/sound-spaces) is with CC-BY-4.0 license. The algorithm of Chaplot *et al*. [2] is implemented based on the publicly released code (https://github.com/devendrachaplot/Object-Goal-Navigation) with MIT license. The algorithm of Krantz *et al*. [25] is implemented based on the publicly released code (https://github.com/jacobkrantz/VLN-CE) with MIT license.

(c) Did you include any new assets either in the supplemental material or as a URL? [N/A] We do not use any new assets excepting the list above.

(d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? [Yes] We obtain Matterport3D [19] data by signing the terms of use (http://kaldir.vc.in.tum.de/matterport/MP_TOS.pdf).

(e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? [Yes] The data used in our paper neither contain any personally identifiable information nor offensive content.

5. If you used crowdsourcing or conducted research with human subjects...

(a) Did you include the full text of instructions given to participants and screenshots, if applicable? [N/A] Our work does not involve any crowdsourcing or conducted research with human subjects.

(b) Did you describe any potential participant risks, with links to Institutional Review Board (IRB) approvals, if applicable? [N/A] Our work does not involve any crowdsourcing or conducted research with human subjects.

(c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? [N/A] Our work does not involve any crowdsourcing or conducted research with human subjects.