## Supplementary Material: Towards Learning a Generic Agent for Vision-and-Language Navigation via Pre-training

**Summary of Contributions.** Weituo implemented the algorithm, made the model work, and ran all experiments. Chunyuan initiated the idea of pre-training the first generic agent for VLN, led and completed the manuscript writing. Xiujun provided the codebase and helped implementation. Lawrence and Jianfeng edited the final manuscript.

## A. Experiments

Three types of inputs on CVDN We illustrate the naming of three types of text inputs on CVDN in Table 6.

	V	$t_0$	$A_i$	$Q_i$	$Q_{1:i-1}\&A_{1:i-1}$
Oracle Answer	$\checkmark$	$\checkmark$	$\checkmark$		
Navigation QA	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	
All	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$	$\checkmark$

Table 6: Three types of inputs on CVDN.  $t_0$  is the target object, V is the ResNet feature.  $Q_i$  and  $A_i$  are the question and answers in the i-th turn.  $Q_{1:i-1}\&A_{1:i-1}$  are the question & answer pairs before the i-th turn.

**Ablation Study Results on HANNA** Table 7 shows the results with different pre-training objectives. We see that the  $\mathcal{L}_{PA} + \mathcal{L}_{MLM}$  yields the best performance among all variants.

	SEEN-ENV				UNSEEN-ALL			
Agent	SR ↑	SPL↑	$NE\downarrow$	#R↓	SR ↑	SPL↑	$\texttt{NE}\downarrow$	#R↓
PREVALENT ( $\mathcal{L}_{PA} + \mathcal{L}_{MLM}$ )	83.82	59.38	1.47	3.4	52.91	28.72	5.29	6.6
PREVALENT ( $\mathcal{L}_{\text{MLM}}$ )	78.75	54.68	1.82	4.3	44.29	24.27	6.33	8.1
BERT (feature-based)	57.54	34.33	4.71	3.9	24.12	11.50	9.55	11.3
BERT (fine-tuning)	80.75	57.46	1.97	4.0	26.36	12.66	9.1	8.3

Table 7: Ablation study of pre-training objectives on test splits of HANNA.

## **B.** Comparison with Related Work

**Comparison with PRESS.** The differences are summarized in Table 8 (a). Empirically, we show that (1) incorporating visual and action information into pre-training can improve navigation performance; (2) Pre-training can generalize across different new navigation tasks.

**Comparison with vision-language pre-training (VLP).** The differences are in Table 8 (b). Though the proposed methodology generally follows self supervised learning such as VLP or BERT, our research scope and problem setups are different, which renders existing pre-models are not readily applicable.

	Prevalent (Proposed)	Press
Dataset	Augmented R2R dataset	Generic language
Modality	Vision-language-action triplets	Language
Learning	Train from scratch	Off-the-shelf (BERT)
Downstream	Three navigation tasks	R2R

	Prevalent (Proposed)	VLP
Visual Input	Panoramic views (Size: 36 × 640 × 480)	Single image (Size: 640 ×480)
Visual Features	ResNet (View-level)	Fast RCNN (Object-level)
Objectives	Attentive MLM & Action Prediction	Masking on VL & Same-Pair Prediction
Downstream RL: Navigation in sequential decision-making environments		Single-step prediction

(a) PRESS (b) VLP

Table 8: Comparison with related works.