

# GeoVLN: Learning Geometry-Enhanced Visual Representation with Slot Attention for Vision-and-Language Navigation

Jingyang Huo\* Qiang Sun\* Boyan Jiang\* Haitao Lin Yanwei Fu Fudan University

THU-PM-249

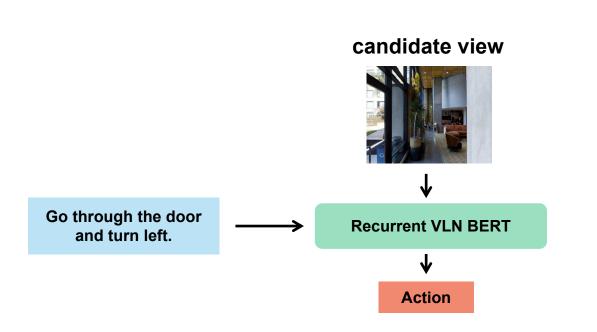
\* Indicates equal contributions.



## **Overview**

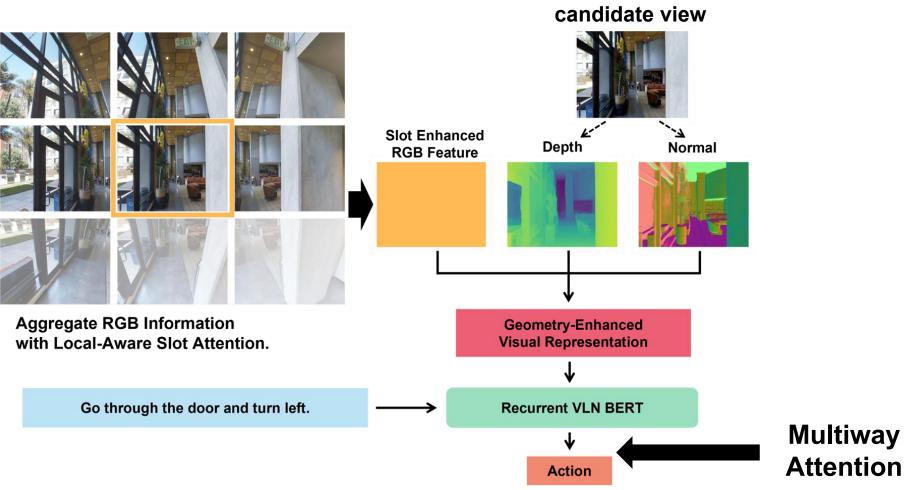
### **Previous Work**

- Utilize RGB images only;  $\succ$
- Lack local spatial context around  $\triangleright$ candidate view.



### **Previous Work**

- $\geq$ Omnidata;
- $\geq$
- $\triangleright$



Compensate RGB images with depth maps and normal maps estimated with

Learn geometry-enhanced visual representation with a two-stage slot-based module; Encourage different phrases of input instruction to focus on the most informative visual observation (e.g. texture, depth) with the multiway attention module.

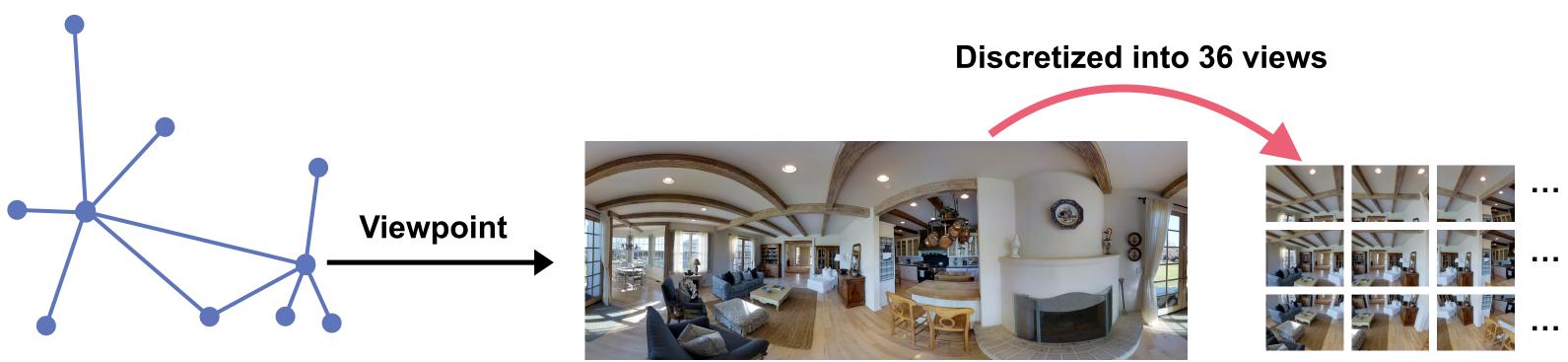
## **VLN** Task

#### **Vision-and-Language Navigation**

Given a natural language instruction, agent makes decision about the next move automatically based on past and current visual observations.



#### **Room-to-Room Navigation Environment**



## **Pipeline**

## Inputs:

- Language Inputs (a user instruction)
- Visual Inputs (a set of visual observations)

#### **BERT**:

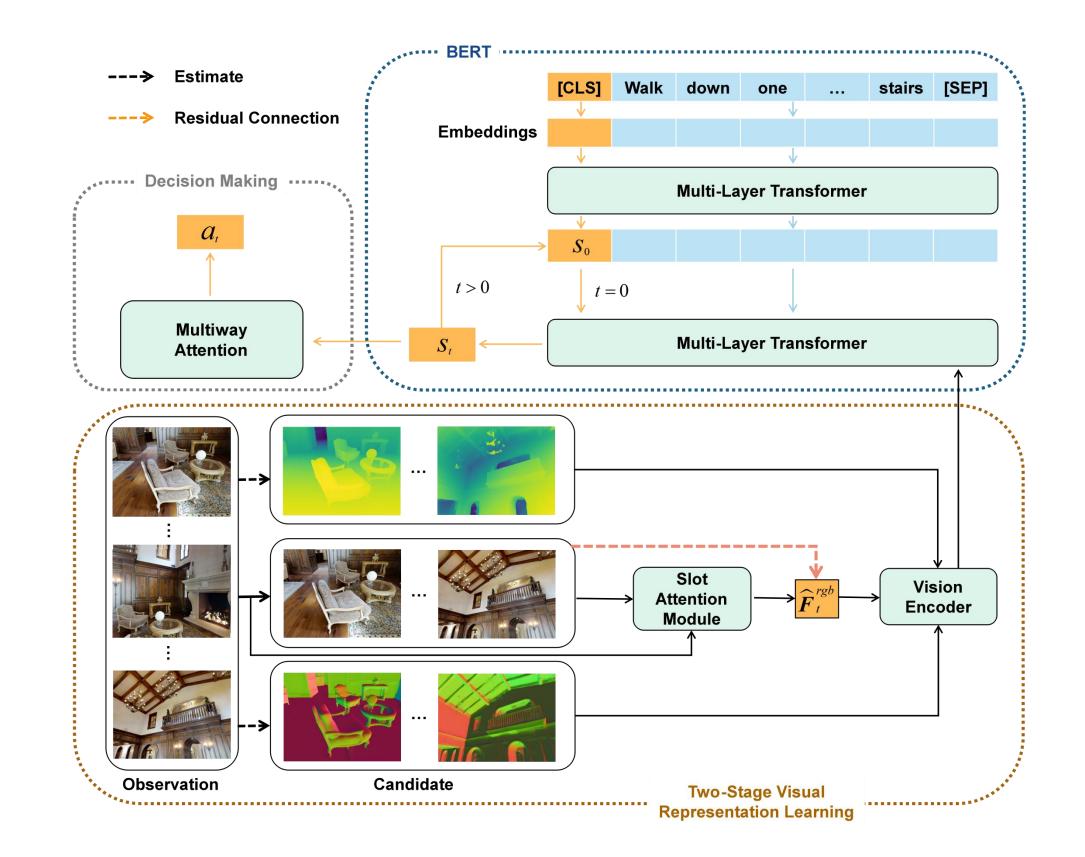
Follow BERT encoder[1] to process the language input and obtain the state vector.

#### **Two-Stage Visual Representation Learning:**

Compensate RGB images with depth maps and normal maps estimated with Omnidata; Learn geometry-enhanced visual representation with a two-stage slot-based module.

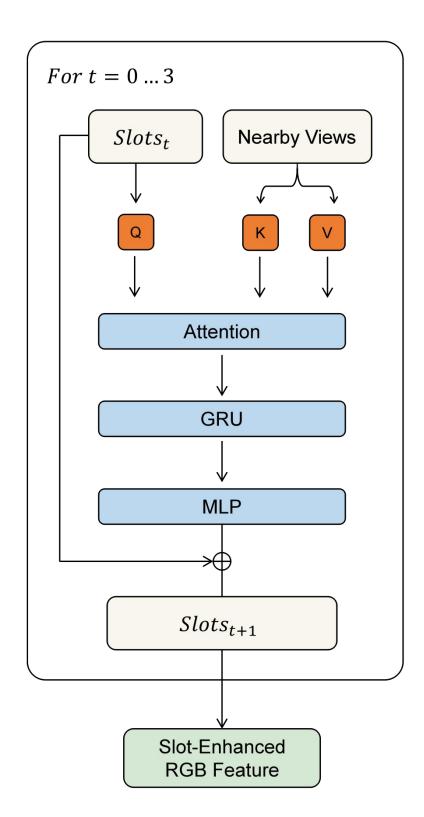
#### **Decision Making:**

Weight matching scores of the three modalities with the multiway attention module.



[1] Yicong Hong, Qi Wu, Yuankai Qi, Cristian Rodriguez Opazo, and Stephen Gould. VIn bert: A recurrent vision-and-language bert for navigation. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition, pages 1643–1653, 2021.

## **Two-Stage Visual Representation Learning**



#### **Visual Features**

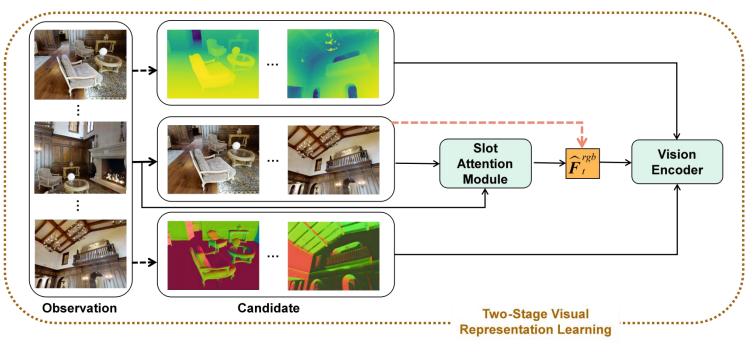
$$\boldsymbol{F}_t^* = [\boldsymbol{C}_t^*; \boldsymbol{F}_t^{ang}], \quad * \in [rgb, dep, nor]$$

#### **Local-Aware Slot Attention**

Make each candidate views aggregate information from the nearby observation views according to the spatial proximity principle.

#### **Geometry-enhanced Visual Representation**

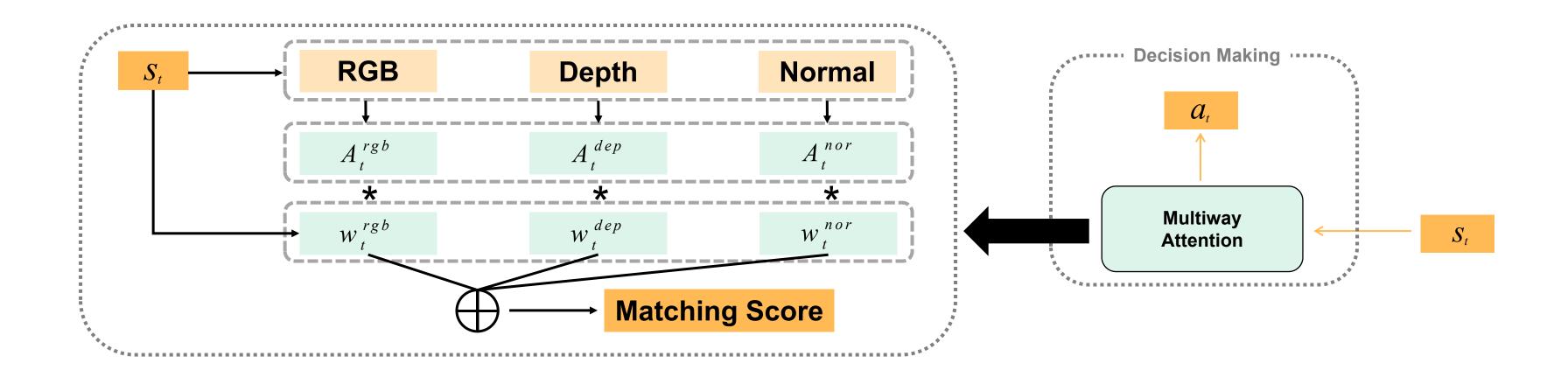
$$\begin{split} \boldsymbol{F}_t &= \left[ \hat{\boldsymbol{F}}_t^{rgb} [...,: d_C]; \boldsymbol{C}_t^{dep}; \boldsymbol{C}_t^{nor}; \boldsymbol{F}_t^{ang} \right] \\ \hat{\boldsymbol{F}}_t &= \mathrm{LN}(\mathrm{FC}(\boldsymbol{F}_t)) \end{split}$$



## **Multiway Attention**

Dynamically weight matching scores of the three modalities with the multiway attention module.

$$\boldsymbol{score}_t^{total} = w_t^{rgb} \boldsymbol{A}_t^{rgb} + w_t^{dep} \boldsymbol{A}_t^{dep} + w_t^{nd}$$





## Main Results

Success Rate (SR): the ratio of agents eventually stopping within 3 meters of the destination; Success Weighted by Path Length (SPL): SR weighted by the inverse of TL. A higher SPL score indicates a better balance between achieving the goal and taking the shortest path.

	Val Seen			Val Unseen			Test Unseen					
Agent	TL↓	NE↓	SR↑	SPL↑	TL↓	NE↓	SR↑	<b>SPL</b> ↑	TL↓	NE↓	SR↑	SPL↑
RANDOM [2]	9.58	9.45	16		9.77	9.23	16	_	9.93	9.77	13	12
Human	-	-	-	_	-	-	-	-	11.85	1.61	86	76
Seq-to-Seq [2]	11.33	6.01	39	1	8.39	7.81	22	-	8.13	7.85	20	18
Speaker-Follower [8]	-	3.36	66	-	-	6.62	35	-	14.82	6.62	35	28
Self-Monitoring [9]	-	-	-	-	-	-	- 1	-	18.04	5.67	48	35
Reinforced Cross-Modal [32]	10.65	3.53	67	-	11.46	6.09	43	-	11.97	6.12	43	38
EnvDrop [30]	11.00	3.99	62	59	10.70	5.22	62	48	11.66	5.23	51	47
AuxRN [37]	-	3.33	70	67	-	5.28	55	50	-	5.15	55	51
PREVALENT [11]	10.32	3.67	69	65	10.19	4.71	58	53	10.51	5.30	54	51
PRESS [18]	10.35	3.09	71	67	10.06	4.31	59	55	10.52	4.53	57	53
AirBERT [10]	11.09	2.68	75	70	11.78	4.01	62	56	12.41	4.13	62	57
VLN 🖒 BERT [15]	11.13	2.90	72	68	12.01	3.93	63	57	12.35	4.09	63	57
<b>GeoVLN (Ours)</b>	11.98	3.17	70	65	11.93	3.51	67	61	13.02	4.04	63	58
HAMT [4]	11.15	2.51	76	72	11.46	2.29	66	61	12.27	3.93	65	60
GeoVLN <sup>†</sup> (Ours)	10.68	2.22	79	76	11.29	3.35	68	63	12.16	3.95	65	61

Table 1. Comparison of **OUR MODEL** with the previous state-of-the-art methods on R2R dataset. <sup>†</sup> indicates the results with HAMT as the backbone. The primary metric is SPL.

## **Ablation Study**

		Input		Val	Seen	Val Unseen		
Model	RGB	DEPTH	NORMAL	SR↑	SPL↑	SR↑	SPL↑	
Baseline	$\checkmark$			69.83	64.21	64.50	58.35	
Baseline	$\checkmark$	$\checkmark$		66.99	63.28	63.86	58.58	
Baseline	$\checkmark$		$\checkmark$	68.46	63.66	62.71	57.20	
Baseline	$\checkmark$	$\checkmark$	$\checkmark$	66.41	62.51	64.75	59.31	
LSA	$\checkmark$			67.58	63.06	64.62	59.78	
LSA	$\checkmark$	$\checkmark$	$\checkmark$	68.66	63.92	66.54	60.62	
LSA + MAtt	$\checkmark$			68.46	63.92	66.11	60.31	
LSA + MAtt (Full)	$\checkmark$	$\checkmark$	$\checkmark$	69.64	64.86	66.75	61.00	

Table 2. Ablation study on multi-modal visual inputs and LSA module with VLN 🖱 BERT as the backbone.

## Visualization

How the **local-aware slot attention** module aggregates local observations to candidate views.









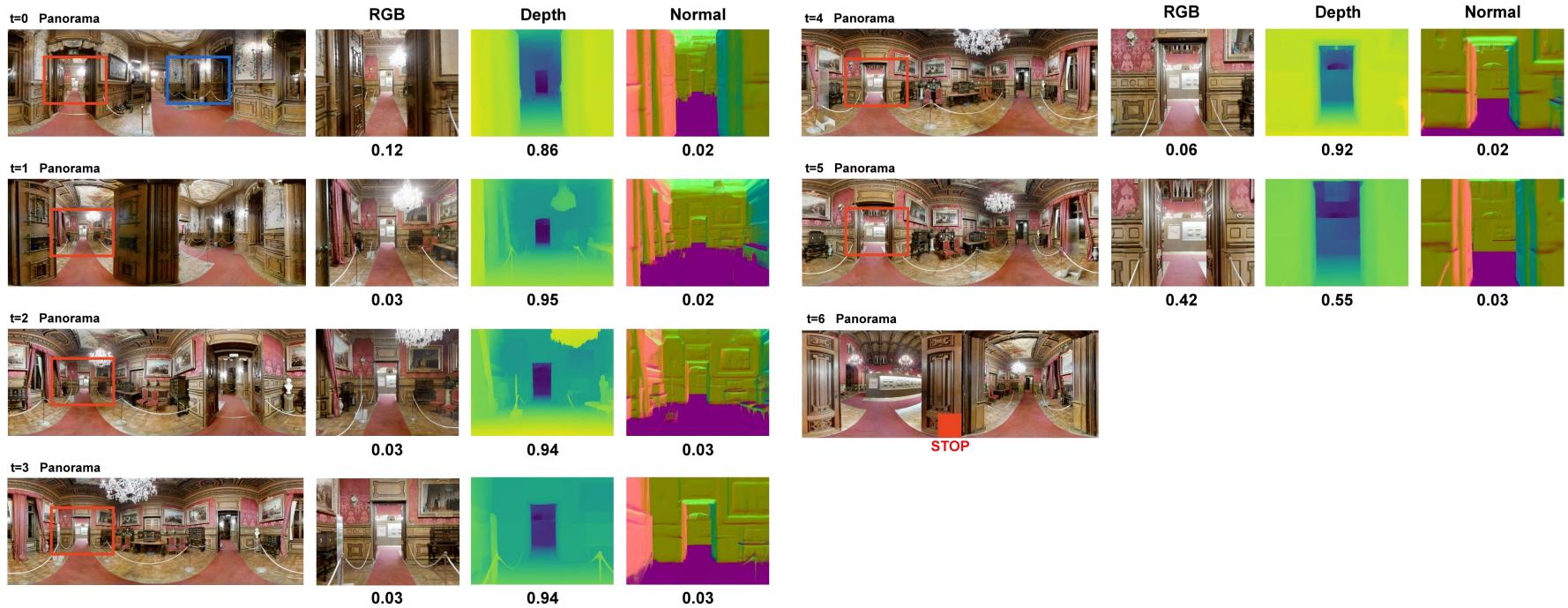
Instruction: "Pass the pool then go into the ....".



Instruction: "Walk up stairs ...".

## Visualization

#### How multiway attention facilitates decision-making.



Instruction: "Follow the red carpet through the double doors. Continue straight through the room and wait in the doorway with the double doors at the end."



# GeoVLN: Learning Geometry-Enhanced Visual Representation with Slot Attention for Vision-and-Language Navigation

Jingyang Huo\* Qiang Sun\* Boyan Jiang\* Haitao Lin Yanwei Fu Fudan University

# Thank you!

\* Indicates equal contributions.

