Grounding Natural Language Processing in Geodata

Raphael Schumann

PhD Student in Computational Linguistics Heidelberg University, Germany



UNIVERSITÄT HEIDELBERG ZUKUNFT SEIT 1386



Geodata

OpenStreetMap

- Natural Language Interface
- Generating Navigation Instructions

Google Street View

- Vision and Language Navigation
- Embodied AI

Introduction OpenStreetMap

OpenStreetMap (OSM) is a free and open geographic database started in 2006.

Applications:

- Map Rendering
- Route Planning
- Geocoding
- Geographic Information Analysis
- and many, many more...



Also serves as a data source for geospatial services of Facebook, Amazon or Apple.

Introduction OpenStreetMap

OpenStreetMap is one gigantic XML file called *planet.osm* (1.8 TB, gzip: 134 GB).

There are three basic components:

Nodes:

point in space defined by latitude and longitude

Ways:

- composed of multiple nodes
- used for: roads, rivers, railway lines, building outlines

Relations:

- group of nodes, ways and other relations
- used for: bus routes, major highways, multipolygons

Any element can be tagged with key-value pairs that specify semantics and metadata.

Overpass Query Language

The Overpass Query Language (OverpassQL) allows to extract elements from OSM:

Desired elements are specified by their type, tags and spatial relationship.

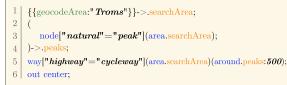
OverpassQL offers extensive syntax features to query, combine and filter geodata.

Motivation Natural Language Interface

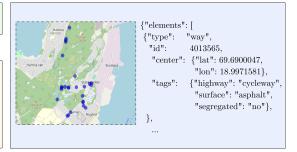
Natural Language Input:

Bike lanes 500 meters around the top of a hill or mountain in Troms.

Overpass Query Language:



Query Execution Results:



Natural Language Interface

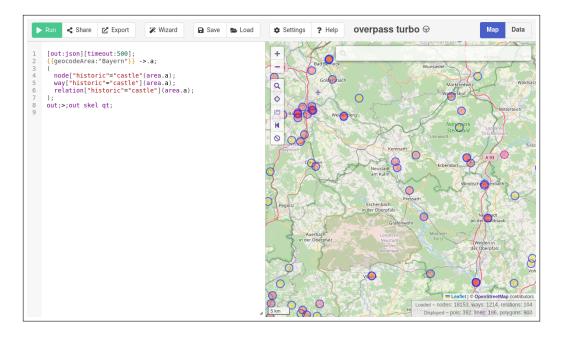
Natural Language Input:



Query Execution Results:

Text-to-OverpassQL: A Natural Language Interface for Complex Geodata Querying of OpenStreetMap Michael Staniek, Raphael Schumann, Maike Züfle, Stefan Riezler TACL 2024

Data Acquisition: https://overpass-turbo.eu



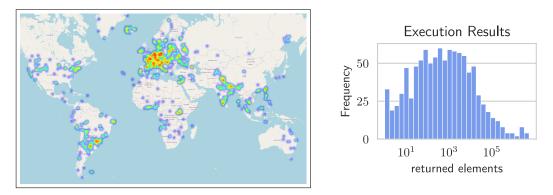
We show the Overpass queries to trained students and ask them to write text inputs.

This has several advantages in comparison to write the queries from scratch:

- Easier to train students to understand Overpass than to write it
- The queries were written to satisfy legitimate information need
- High feature coverage because written by proficient users

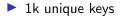
OverpassNL Dataset: Statistics

${\bf 8.5k}$ Overpass queries with annotated natural language input

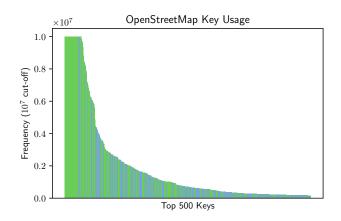


Large location coverage and up to 10^7 elements returned when executing a query.

OverpassNL Dataset: Statistics



- ▶ 90% of key usage in OSM
- 3.9k unique values
- 4.9k unique key-value pairs



Dataset	Query	Named Identifiers		Extrac	Results	
Dutubet	Language	total	per database	total	per database	per query
Spider	SQL	4,669 & 876	58 & 5	1.6M	9.6k	30
OverpassNL	OverpassQL	1,046	1,046	9B	9B	10k

In OverpassNL, each query can utilize any key-value pair (named identifier) and retrieve elements from the entire OSM database.

In Text-to-SQL, each individual database is muss smaller which reduces the number of relevant table/column names (named identifier) significantly.

Text-to-OverpassQL: Results

Model	String Match	Execution Accuracy
OverpassT5	22.0	36.7
GPT-3	19.5	34.1
GPT-4	23.4	40.4

Evaluated on 1,000 dev instances.

Finetuned T5 Model

- 6.5k training instances
- +8k from code comments
- ByT5 is better than CodeT5

In-Context Learned GPT Models

- 5-Shot In-Context Learning
- retrieval by text similarity
- sBERT cosine is better than BLEU

Model	chrF	KVS	TreeS	Execution Accuracy
OverpassT5	75.5	66.0	73.7	36.7
GPT-4	75.7	69.9	74.0	40.4

- chrF: Character F-score [Popović 2015]
- **KVS**: Key-Value Similarity Normalized overlap of key-value
- ► TreeS: XML-Tree Similarity Subtree overlap of query in XML representation

Text-to-OverpassQL: Results

Model	chrF	KVS	TreeS	Execution Accuracy
OverpassT5 GPT-4	75.5	66.0	73.7	36.7
GPT-4	75.7	69.9	74.0	40.4

- chrF: Character F-score [Popović 2015]
- **KVS**: Key-Value Similarity Normalized overlap of key-value
- ► TreeS: XML-Tree Similarity Subtree overlap of query in XML representation

Model	# Syntax Errors	Execution Accuracy
GPT-4	24	40.4
refine w/o feedback	31	39.6
refine with feedback	26	41.4

Feedback is the error message or a sample of the returned results.

Demo: https://overpassnl.schumann.pub



Generating Navigation Instructions

If you ask a person on the street for directions, they give you a different type of navigation instructions than a GPS system or routing app.

GPS system:

- turn-by-turn with exact distances
- street names

Human-like:

- colloquially
- Iandmark based
- easier to memorize

Generating Human-like Navigation Instructions

Existing systems that generate landmark-based navigation instructions:

- rule-based landmark selection
- hand-crafted salience scores
- template-based text generation

 \rightarrow End-to-end system that learns to select landmarks and generate instructions

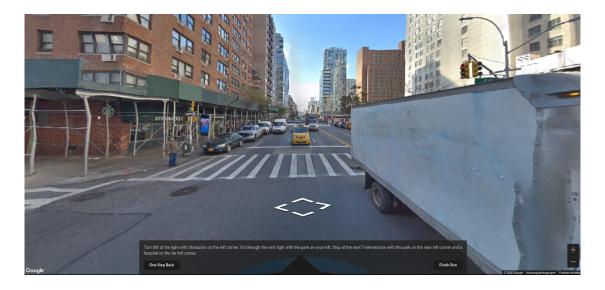
Generating Landmark Navigation Instructions from Maps as a Graph-to-Text Problem Raphael Schumann and Stefan Riezler ACL 2021

Navigation Instructions - Data Collection



Submit

Navigation Instructions - Data Collection



Navigation Instructions - Data Collection



The New York Foundation 183

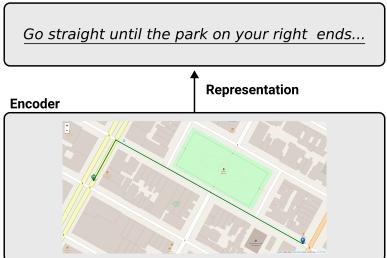
verified

failed

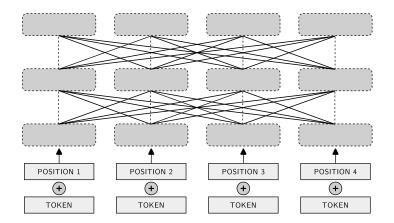
- ▶ Paid \$0.35 (+\$0.25 bonus) per writing task and \$0.20 (+\$0.15 bonus) per navigation task
- ► Collected 7.5k verified navigation instructions for around \$10k in total

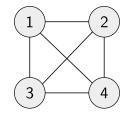
Route Representation

Text Decoder



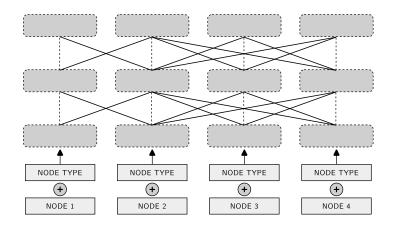
Graph Encoder

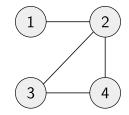




Vanilla Transformer Encoder [Vaswani et al. 2017]

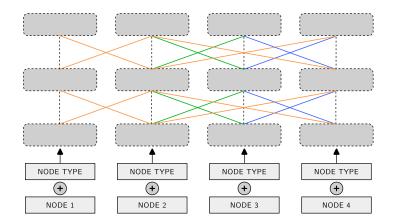
Graph Encoder

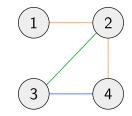




Graph Attention Networks [Veličković et al. 2018]

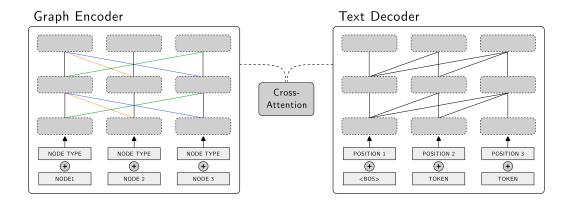
Graph Encoder



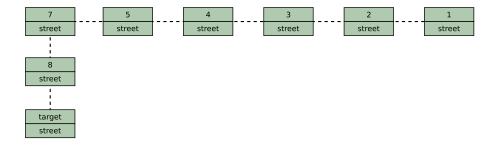


Labeled Edges [Schlichtkrull et al. 2018]

Graph-to-Text

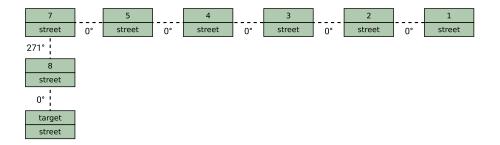


NODE TOKEN NODE TYPE

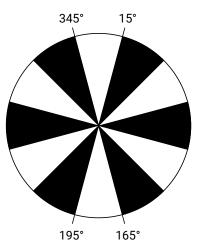


Go straight until the park on your right ends and turn left. Continue and stop with Starbucks on your left.

NODE TOKEN NODE TYPE



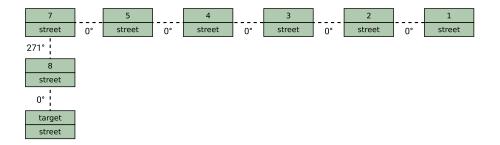
Go straight until the park on your right ends and turn left. Continue and stop with Starbucks on your left.



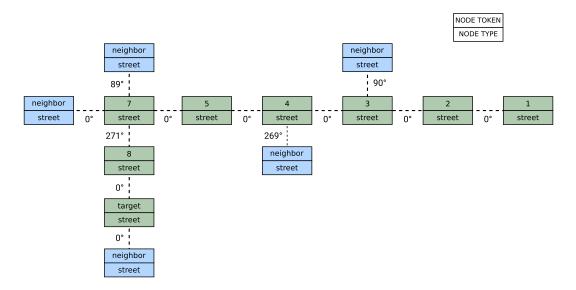
• discretize angles into 12 bins with 30° each

label edges with angles according to angle bin

NODE TOKEN NODE TYPE

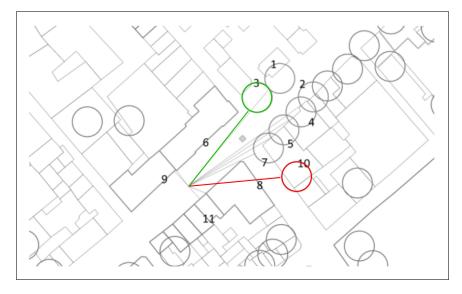


Go straight until the park on your right ends and turn left. Continue and stop with Starbucks on your left.

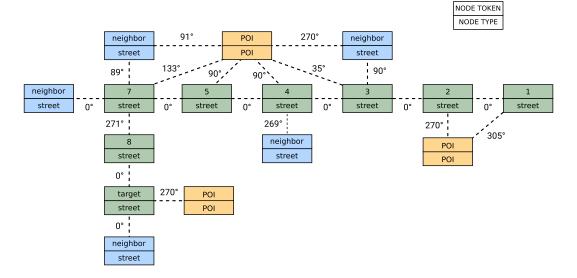


Go straight until the park on your right ends and turn left. Continue and stop with Starbucks on your left.

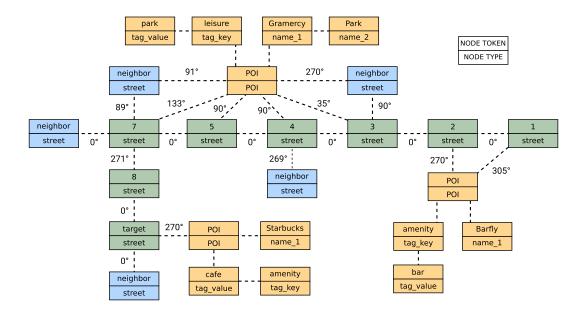
POI Visibility



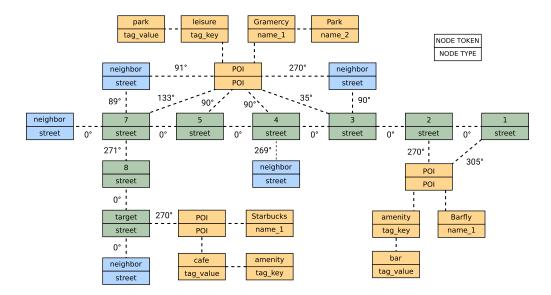
[Rousell et al. 2015]



Go straight until the park on your right ends and turn left. Continue and stop with Starbucks on your left.



Go straight until the park on your right ends and turn left. Continue and stop with Starbucks on your left.

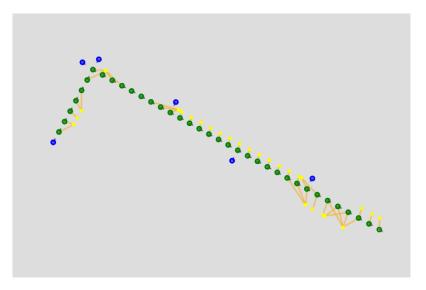


translation and rotation invariant \rightarrow helps generalization



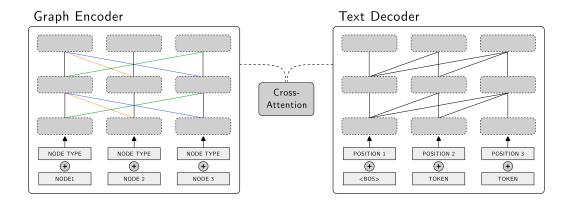






On average, 144 nodes per graph and 4.3 edges per node.

Graph-to-Text



Generating Human-like Navigation Instructions

	Human Navigation Success
rule-based	46%
seq2seq	16%
graph2text	54%

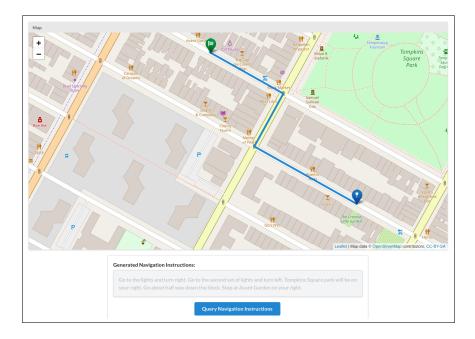
We also analyze the landmarks selected by the graph2text model and find that they closely follow the distribution of reference landmarks.

Example of Generated Instructions

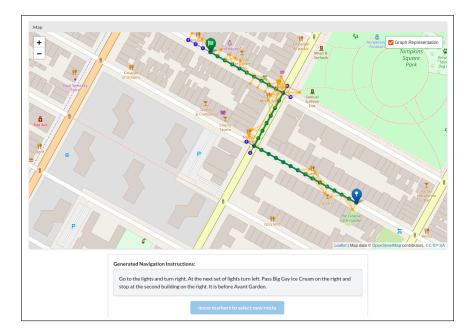


Go to the light and turn right. Go straight through 1 light and at the following light, there should be a bus stop on the far left corner. Turn left and go about 1/2 to the next light, stopping in front of Saint Patrick's church on the right and graveyard Memorial's on the right.

Demo: https://map2seq.schumann.pub/nllni/demo/



Demo: https://map2seq.schumann.pub/nllni/demo/



Vision and Language Navigation

Any question so far?

Agent Embodiment:



Action Space:

FORWARD LEFT RIGHT STOP

Navigation Instructions:

"Pass the bike rental and turn left at the lights. Go to the third set of lights with HSBC on the left and turn left. Stop just after Maison Kayser on the left."

Touchdown Environment:

[Chen et al. 2019]

- 30k panorama images
- Connectivity graph
- Lower Manhattan
- 10k navigation instructions



Touchdown:

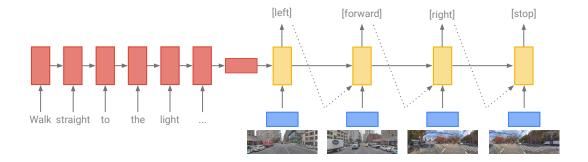
Orient yourself with the flow of traffic, a clear awning to your left and green door to the right. Travel down this street all the way to the traffic light ahead and turn right. Stop at the store with a green and white sign to your right.

- path length: 35-45 nodes (with shorter outlier)
- instructions length: 89 tokens

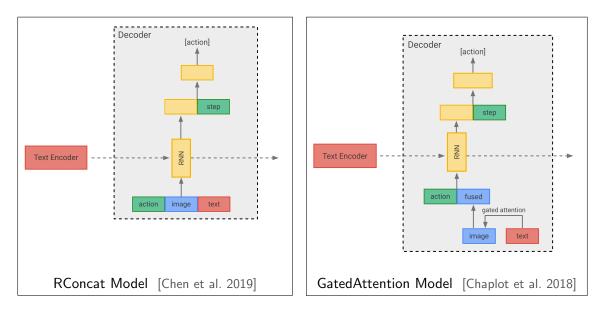
Map2seq:

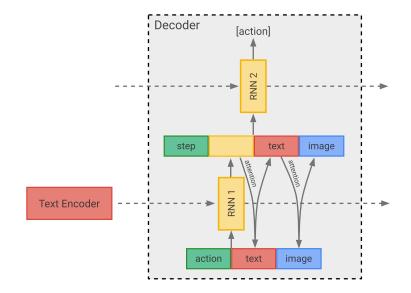
<u>Head all the way down the block</u> and with a <u>Chase</u> on the far right corner, make a right. Head through the next two lights, passing <u>Banh Mi Saigon</u> on the right and then stop in the middle of the next light.

- shortest path
- ▶ path length: 35-45 nodes
- instructions length: 55 tokens



VLN as sequence-to-sequence model with RNN encoder and decocer.





ORAR Model [Schumann and Riezler 2022]

Model	тс
RConcat [Chen et al. 2019]	13.3
GatedAttention [Chaplot et al. 2018]	14.5
VLN Transformer [Zhu et al. 2021]	16.0
ORAR [Schumann and Riezler 2022]	34.7

Task completion (TC) measures weather the agent stopped at the target location.

In the slides, I report the mean TC on Touchdown and map2seq navigation instances.



Analyzing Generalization of Vision and Language Navigation to Unseen Outdoor Areas Raphael Schumann and Stefan Riezler ACL 2022

Model	TC (Seen)	TC (Unseen)
RConcat [Chen et al. 2019]	13.3	2.0
Gated-Attention [Chaplot et al. 2018]	14.5	2.0
VLN Transformer [Zhu et al. 2021]	16.0	3.3
ORAR [Schumann and Riezler 2022]	34.7	4.6

The task completion rate in the unseen scenario collapses for all models.

In that scenario, the evaluation area is geographically separated from the training area.





Model	TC (Seen)	TC (Unseen)
ORAR	34.7	4.6
+ junction	37.1	19.2

Model	TC (Seen)	TC (Unseen)
ORAR	34.7	4.6
+ junction	37.1	19.2
+ heading delta	37.9	22.6

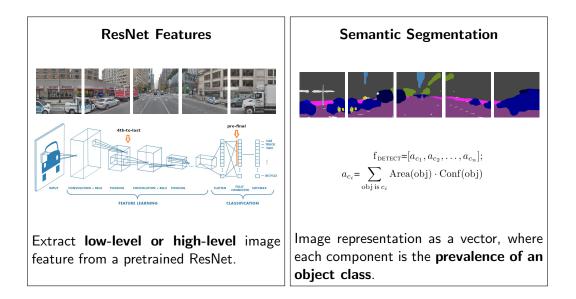


Image	TC (Seen)	TC (Unseen)
no image	26.0	20.0
semantic segmentation	33.2	21.1
ResNet (high level)	36.0	16.7
ResNet (low level)	35.4	22.6

Image	TC (Seen)	TC (Unseen)
no image	26.0	20.0
semantic segmentation ResNet (high level) ResNet (low level)	33.2 36.0 35.4	21.1 16.7 22.6
fixed random vector	32.5	18.2

Fixed random vector as representation of each panorama image.

Verbalization Embodiment

Motivation: Use LLMs as the reasoning engine for embodied agents in Street View.

Challenges:

Integrate visual observations into text interface

Advantages:

- unlocks few-shot learning
- no over-fitting to image features
- evaluation task for egocentric spatial-reasoning of LLMs

VELMA: Verbalization Embodiment of LLM Agents for VLN in Street View Raphael Schumann, Wanrong Zhu, Weixi Feng, Tsu-Jui Fu, Stefan Riezler, William Yang Wang AAAI 2024

Verbalization Embodiment - Text Interface

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Orientate yourself such that a blue bench is on your right, go to the end of the block and make a right. Follow the park on your left and make a right at the intersection. Pass the **black fire hydrant** on your right and stop when you get to a gray door on the brown building." Action Sequence: There is a blue bench on your left. 1. turn around There is a blue bench on your right. 2. forward There is a 3-way intersection. 3. right 4. forward There is a park on your left. 5. forward There is a park on your left. 6. forward There is a 4-way intersection. 7. <*next word prediction*>

Write a list of visible landmarks mentioned in the navigation instructions:

Go straight down the road and turn right at the next intersection. Go straight until there is a *Starbucks* on your right and turn left at the following intersection with the *bicycle rental* at the corner. Continue down the block and stop when *a church* is on your left.

- 1. Starbucks
- 2. a bike rental
- 3. a church

Prompt to extract landmarks mentioned in the navigation instructions. The list in blue is generated by the LLM.

Prompt Sequence

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Go straight down the road and turn right at the next intersection. Go straight until there is a **Starbucks** on your right and turn left at the following intersection with the **bicycle rental** at the corner. Continue down the block and stop when **a church** is on your left." Action Sequence:

1. forward

2. forward

There is a 4-way intersection.

3. right

4. forward

5. forward

6. forward

Environment



Extracted Landmarks

- Starbucks
- a bicycle rental
- a church

Prompt Sequence

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Go straight down the road and turn right at the next intersection. Go straight until there is a **Starbucks** on your right and turn left at the following intersection with the **bicycle rental** at the corner. Continue down the block and stop when **a church** is on your left." Action Sequence:

1. forward

2. forward

There is a 4-way intersection.

- 3. right
- 4. forward
- 5. forward
- 6. forward

Environment



Panorama & Heading



Extracted Landmarks

- Starbucks
- a bicycle rental
- a church

Prompt Sequence

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Go straight down the road and turn right at the next intersection. Go straight until there is a **Starbucks** on your right and turn left at the following intersection with the **bicycle rental** at the corner. Continue down the block and stop when **a church** is on your left." Action Sequence:

1. forward

2. forward

There is a 4-way intersection.

- 3. right
- 4. forward
- 5. forward
- 6. forward

Environment



Extracted Landmarks

- Starbucks
- a bicycle rental
- a church

Landmark Detection

Prompt Sequence

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Go straight down the road and turn right at the next intersection. Go straight until there is a **Starbucks** on your right and turn left at the following intersection with the **bicycle rental** at the corner. Continue down the block and stop when **a church** is on your left." Action Sequence:

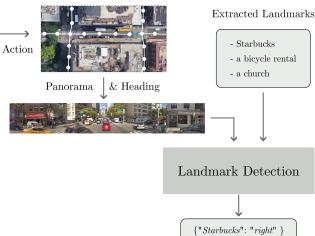
1. forward

2. forward

There is a 4-way intersection.

- 3. right
- 4. forward
- 5. forward
- 6. forward

Environment



Prompt Sequence

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Go straight down the road and turn right at the next intersection. Go straight until there is a **Starbucks** on your right and turn left at the following intersection with the **bicycle rental** at the corner. Continue down the block and stop when **a church** is on your left." Action Sequence:

1. forward

2. forward

There is a 4-way intersection.

3. right

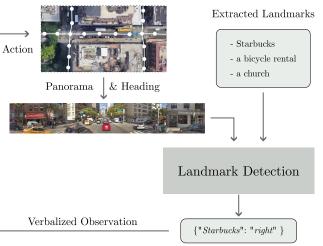
4. forward

5. forward

6. forward

There is a Starbucks on your right.

Environment



Prompt Sequence

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Go straight down the road and turn right at the next intersection. Go straight until there is a **Starbucks** on your right and turn left at the following intersection with the **bicycle rental** at the corner. Continue down the block and stop when **a church** is on your left." Action Sequence:

1. forward

2. forward

There is a 4-way intersection.

3. right

4. forward

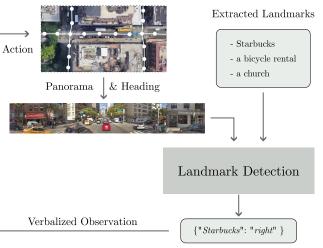
5. forward

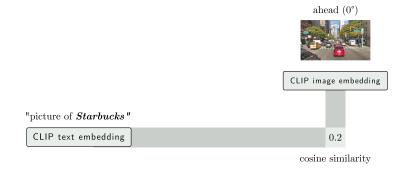
6. forward

There is a Starbucks on your right.

7. < next word prediction >

Environment





	left	(-90°)	slightl	y left	(-45°)	ahe	ead $(0$	°)	slightly	righ	t (45°)	rig	ht (90	°)
													STARBUS	
	CLIP i	mage emb	. CLIP	image	emb.	CLIP	image	emb.	CLIP i	image	emb.	CLIP	image	emb.
"picture of <i>Starbucks</i> "														
CLIP text embedding		0.5		0.3			0.2			0.6			0.8	

	left (-	90°)	slightl	y left	(-45°)	$^{\rm ah}$	ead (0°)	slightly	righ	nt (45°)	rig	ht (90)°)
													STARBU	
	CLIP ima	ge emb.	CLIP	image	e emb.	CLIP	image	emb.	CLIP	image	e emb.	CLIP	image	emb.
"picture of <i>Starbucks</i> "														
CLIP text embedding	0.	5		0.3			0.2			0.6			0.8	
"picture of <i>a church</i> "														
CLIP text embedding) 0.	3		0.5			0.4			0.3			0.2	

	left	(-90°)	slightly	left $(-4$	5°) ah	ead (0)°)	slightly	righ	t (45°)	righ	it (90	°)
												STARBUC	
	CLIP in	nage emb	CLIP i	mage em	b. CLIP	image	emb.	CLIP i	mage	emb.	CLIP in	nage (emb.
"picture of <i>Starbucks</i> "													
CLIP text embedding		0.5		0.3		0.2			0.6			0.8	
"picture of <i>a church</i> "													
CLIP text embedding] (0.3		0.5		0.4			0.3			0.2	
"picture of <i>a bike rent</i>	al"												
CLIP text embedding		0.2		0.3		0.2			0.4			0.6	

	left $(-9$	0°) slightly	left (-45°)	ahead (0°)	slightly right (45°)	right (90°)
	CLIP image	e emb. CLIP i	mage emb.	CLIP image emb	CLIP image emb.	CLIP image emb.
"picture of <i>Starbucks</i> "						
CLIP text embedding	0.5		0.3	0.2	0.6	0.8
"picture of <i>a church</i> "						
CLIP text embedding	0.3		0.5	0.4	0.3	0.2
"picture of <i>a bike rent</i>	al"					
CLIP text embedding	0.2		0.3	0.2	0.4	0.6

Verbalization Embodiment - Pipeline

Prompt Sequence

Navigate to the described target location! Action Space: forward, left, right, turn_around, stop Navigation Instructions:

"Go straight down the road and turn right at the next intersection. Go straight until there is a **Starbucks** on your right and turn left at the following intersection with the **bicycle rental** at the corner. Continue down the block and stop when **a church** is on your left." Action Sequence:

1. forward

2. forward

There is a 4-way intersection.

3. right

4. forward

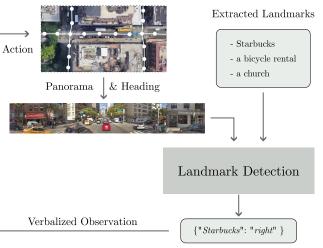
5. forward

6. forward

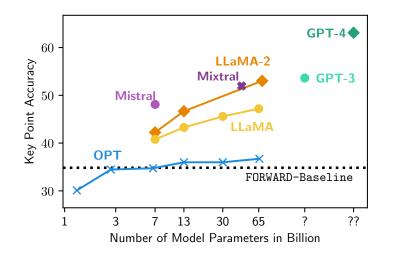
There is a Starbucks on your right.

7. < next word prediction >

Environment



2-Shot In-context Learning



Model	TC (unseen)
Mixtral	7.3
GPT-3	8.0
GPT-4	16.6

Model	TC (unseen)
ORAR	25.2
VELMA-FT	31.8

VELMA-FT is LLaMA-7b finetuned on the full training set. Die finetuning text is the full verbalized trajectory prompt along the gold path.

Model	TC (unseen)
ORAR	25.2
VELMA-FT	31.8
VELMA-FT (no image)	26.4

VELMA-FT (no image) does not receive verbalized visual observations.

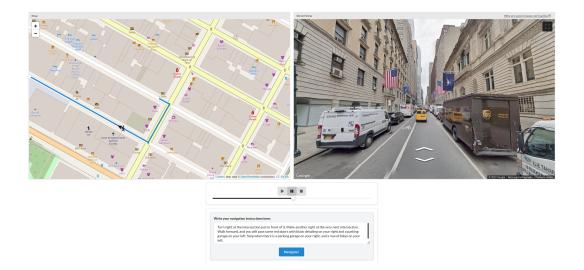
Model	TC (unseen)
ORAR	25.2
VELMA-FT	31.8
VELMA-RBL	37.0

Algorithm 1: RBL Optimization of Task Completion
Require: mixing ratio λ , training step j, model weights θ_j ,
gold action sequence $\hat{\mathbf{a}}$, prompt x_1
if $random(0,1) < \lambda$ then
$\mathbf{a}_{\theta_j} = StudentForcing(\theta_j, x_1)$
$\mathbf{a}_j = rg \max \mathbf{a}_{\theta_j}$
if $TaskCompletion(\mathbf{a}_i) = 1$ then
$loss_j = \mathcal{L}_{CE}(\mathbf{a}_{ heta_j}, \mathbf{a}_j)$
else
$\mathbf{a}_{j}^{*} = Oracle_{stepwise}(\mathbf{a}_{j})$
$\hat{loss_j} = \mathcal{L}_{CE}(\mathbf{a}_{ heta_j}, \mathbf{a}^*_j)$
end if

else

$$\begin{split} \mathbf{a}_{\theta_j} &= TeacherForcing(\theta_j, x_1, \hat{\mathbf{a}})\\ loss_j &= \mathcal{L}_{CE}(\mathbf{a}_{\theta_j}, \hat{\mathbf{a}})\\ \text{end if} \end{split}$$

Demo: https://velma.schumann.pub





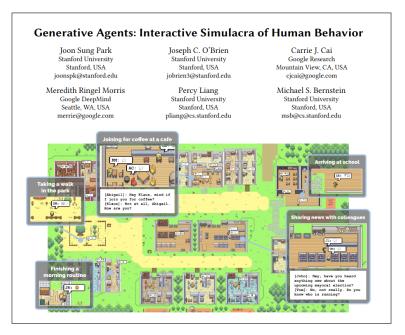
Raphael Schumann @RaphiRaph_

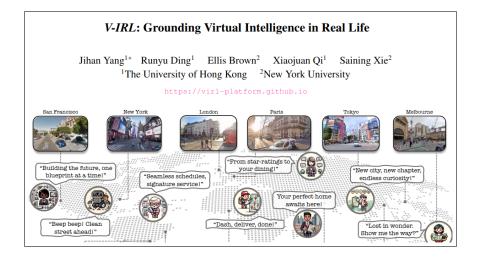
IMHO: OpenStreetMap is underused as a resource in the NLP community. It stores vast amount of knowledge about the real-world that is hard to pick up from text documents only. It can also underpin environments for LLM agent simulations.

...

#NLProc #GIS #GISchat #NLP #LLMs #OverpassQL

7:05 AM · Aug 31, 2023





End

End

Bibliography I

Chaplot, Devendra Singh et al. (2018). "Gated-Attention Architectures for Task-Oriented Language Grounding". In: *Proceedings of the AAAI Conference on Artificial Intelligence (AAAI)*. New Orleans, Louisiana.
Chen, Howard et al. (2019). "TOUCHDOWN: Natural Language Navigation and

Spatial Reasoning in Visual Street Environments". In: *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR)*. Long Beach, California.

Popović, Maja (Sept. 2015). "chrF: character n-gram F-score for automatic MT evaluation". In: Proceedings of the Tenth Workshop on Statistical Machine Translation. Lisbon, Portugal: Association for Computational Linguistics, pp. 392–395.

Rousell, Adam et al. (June 2015). "Extraction of landmarks from OpenStreetMap for use in navigational instructions". In.

Schlichtkrull, Michael et al. (2018). "Modeling Relational Data with Graph Convolutional Networks". In: *The Semantic Web*. Ed. by Aldo Gangemi et al. Cham: Springer International Publishing, pp. 593–607. Schumann, Raphael and Stefan Riezler (May 2022). "Analyzing Generalization of Vision and Language Navigation to Unseen Outdoor Areas". In: Proceedings of the 60th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers). Dublin, Ireland: Association for Computational Linguistics, pp. 7519–7532.

Vaswani, Ashish et al. (2017). "Attention is All you Need". In: Advances in Neural Information Processing Systems. Ed. by I. Guyon et al. Vol. 30. Curran Associates, Inc.

Veličković, Petar et al. (2018). "Graph Attention Networks". In: International Conference on Learning Representations.

 Zhu, Wanrong et al. (Apr. 2021). "Multimodal Text Style Transfer for Outdoor Vision-and-Language Navigation". In: Proceedings of the 16th Conference of the European Chapter of the Association for Computational Linguistics: Main Volume. Online: Association for Computational Linguistics, pp. 1207–1221.