Grounding Complex Natural Language Commands for Temporal Tasks in Unseen Environments: Supplementary Material

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1 Specification Patterns

We developed Lang2LTL to ground navigational commands to LTL formulas. We started with the catalog of robotic mission-relevant LTL patterns for robotic missions by Menghi et al. [1]. We adopted 15 templates that are relevant to robot navigation and modified some of their patterns to semantically match our requirements. The complete list of pattern descriptions and the corresponding LTL templates is in Table 4. Note that we use some additional abbreviated temporal operators, specifically "Weak until" $\mathbf{W}$, and the "Strong release" $\mathbf{M}$ in terms of standard operators, i.e., $a \mathbf{W} b = a \mathbf{U} (b \vee \mathbf{G} a)$, and $a \mathbf{M} b = b \mathbf{U} (a \wedge b)$.

2 Semantic Information from OpenStreetMap Database

We show an example entry of the semantic dataset as follows,

```
{
    "Jiaho supermarket": {
        "addr:housenumber": "692",
        "shop": "supermarket",
        "opening_hours": "Mo-Su 08:00-20:00",
        "phone": "6173389788",
        "addr:postcode": "02111",
        "addr:street": "Washington Street"
    },
    ...,
}
```

3 Implementation Details about Referring Expression Generation

We prompt the GPT-4 model for paraphrasing landmarks with corresponding OSM databases. For each landmark, three referring expressions are generated. The prompt for generating referring expressions by paraphrasing is as follows,

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7th Conference on Robot Learning (CoRL 2023), Atlanta, USA.

Use natural language to describe the landmark provided in a python dictionary form in a short phrase.

Landmark dictionary:
'Fortuna Cafe': {'addr:housenumber': '711', 'cuisine': 'chinese', 'amenity': 'restaurant', 'addr:city': 'Seattle', 'addr:postcode': '98104', 'source': 'King County GIS;data.seattle.gov', 'addr:street': 'South King Street'}
Natural language:
Chinese cafe on South King Street

Landmark dictionary:
'Seoul Tofu House & Korean BBQ': {'addr:housenumber': '516', 'cuisine': 'korean', 'amenity': 'restaurant', 'addr:city': 'Seattle', 'addr:postcode': '98104', 'source': 'King County GIS;data.seattle.gov', 'addr:street': '6th Avenue South'}
Natural language:
Seoul Tofu House

Landmark dictionary:
'AI Video': {'shop': 'electronics'}
Natural language:
AI Video selling electronics

...

Landmark dictionary:
'Dochi': {'addr:housenumber': '604', 'cuisine': 'donut', 'amenity': 'cafe'}

Natural language:
a cafe selling donut named Dochi

Landmark dictionary:
'AVA Theater District': {'addr:housenumber': '45', 'building': 'residential', 'building:levels': '30'}
Natural language:
AVA residential building

Landmark dictionary:
'HI Boston': {'operator': 'Hosteling International', 'smoking': 'no', 'wheelchair': 'yes', 'tourism': 'hostel'}
Natural language:
HI Boston

Landmark dictionary:

4 Implementation Details about Referring Expression Recognition

The prompt for referring expression recognition is as follows,

Your task is to repeat exact strings from the given utterance which possibly refer to certain propositions.

Utterance: move to red room
Propositions: red room

Utterance: visit Cutler Majestic Theater
Propositions: Cutler Majestic Theater

Utterance: robot c move to big red room and then move to green area
Propositions: big red room | green area

Utterance: you have to visit Panera Bread on Beacon Street, four or more than four times
Propositions: Panera Bread on Beacon Street

Utterance: go to Cutler Majestic Theater at Emerson College on Tremont Street, exactly three times
Propositions: Cutler Majestic Theater at Emerson College on Tremont Street

...

Utterance: make sure you never visit St. James Church, a Christian place of worship on Harrison Avenue, Dunkin' Donuts, Thai restaurant Montien, New Saigon Sandwich, or Stuart St @ Tremont St
Propositions: St. James Church, a Christian place of worship on Harrison Avenue | Dunkin' Donuts | Thai restaurant Montien | New Saigon Sandwich | Stuart St @ Tremont St

Utterance: move the robot through yellow region or small red room and then to large green room
Propositions: yellow region | small red room | large green room

Utterance:

The results of using this prompt to recognize referring expressions with spatial relations are shown in Table 6.

5 Implementation Details about Lifted Translation

5.1 Fintuned T5-Base

For finetuning the T5-Base model, we set the batch size to 40, the learning rate to 10^{-4}, and the weight decay to 10^{-2}. We ran training for 10 epochs and picked the best-performing one for reporting results.

5.2 Finetuned GPT-3

The per specification type accuracies and the accuracies for varying number of propositions in the formula while testing the finetuned GPT-3 model on the utterance holdout is depicted in Figure **??**. The finetuned GPT-3 model achieves high accuracies across formula types and varying numbers of propositions. It shows the benefit of having a large high-quality dataset of natural language commands representing diverse LTL formulas. All previous works also used utterance holdout as their testing methodology, but their training and test sets contain significantly fewer unique LTL formulas.

5.3 Prompt GPT-4

The prompt for end-to-end GPT-4 is as follows,

```
Your task is to translate English utterances into linear temporal logic (LTL) formulas.

Utterance: visit b
LTL: F b

Utterance: eventually reach b and h
LTL: & F b F h

Utterance: go to h a and b

LTL: & F h & F a F b

Utterance: proceed to reach h at the next time instant only and only if you see b
LTL: G e b X h

Utterance: wait at b till you see h
LTL: U b h

Utterance: go to h in the very next time instant whenever you see b
LTL: G i b X h

Utterance:
```

5.4 Prompt GPT-3

The prompt for end-to-end GPT-3 is the same as the one we used for Prompt GPT-4.

5.5 Seq2Seq Transformer

We constructed and trained a transformer model following [2]. More specifically, we built the model's encoder with three attention layers and decoder with three layers, and we used 512 as the embedding size and 8 as the number of attention heads. For training, we adapted batched training with a batch size equal to 128, learning rate equal to 10^{-4}, and dropout ratio equal to 0.1; the training process runs for 10 epochs, and we picked the best-performing checkpoint for baseline comparison.

5.6 Type Constrained Decoding (TCD)

Constrained decoding has been used in generating formal specifications for eliminating syntactically invalid outputs. Due to the sampling nature of NN-based models, generated tokens from the output layer can result in syntactical errors that can be detected on the fly, and type-constrained decoding solves it by forcing the model to only generate tokens following the correct grammar rule. By eliminating syntax errors, it also improves the overall performance of the system.

In practice, type-constrained decoding is implemented at each step of the decoding loop: first checking the validity of the output token, then appending the valid token or masking the invalid, and re-generating a new token according to the probability distribution after masking. In addition, we design an algorithm to simultaneously enforce the length limitation and syntactical rule by parsing partial formulas into binary trees. Beyond a given maximum height of the tree, the model is forced only to generate propositions but not operators.

6 Implementation Details about Code as Policies

We designed two prompts for reproducing Code as Policies: one for code generation and the other for parsing landmarks. The code generation prompt is expected to generate an executable Python script that calls the goto_loc() function for traversing through the environment and psrse_loc() function to ground referring expressions to landmarks, where the landmark resolution prompt is used. The code generation prompt for graph search is as follows,

```
# Python 2D robot navigation script

import random
from utils import goto_loc, parse_loc

# make the robot go to wooden desk.
target_loc = parse_loc('wooden desk')
goto_loc(target_loc)
# go to brown desk and then white desk.
target_loc_1 = parse_loc('brown desk')
target_loc_2 = parse_loc('white desk')
target_locs = [target_loc_1, target_loc_2]
for target_loc in target_locs:
  goto_loc(target_loc)
# head to doorway, but visit white kitchen counter before that.
target_loc_1 = parse_loc('white kitchen counter')
target_loc_2 = parse_loc('doorway')
target_locs = [target_loc_1, target_loc_2]
for target_loc in target_locs:
  goto_loc(target_loc)
# avoid white table while going to grey door.
target_loc = parse_loc('grey door')
avoid_loc = parse_loc('white table')
target_locs = [target_loc]
avoid_locs = [avoid_loc]
for loc in target_locs:
  goto_loc(loc, avoid_locs=avoid_locs)
# either go to steel gate or doorway
target_loc_1 = parse_loc('steel gate')
target_loc_2 = parse_loc('doorway')
target_locs = [target_loc_1, target_loc_2]
target_loc = random.choice(target_locs)
goto_loc(target_loc)

...

# go to doorway three times
target_loc = parse_loc('doorway')
for _ in range(3):
  goto_loc(target_loc)
  random_loc = target_loc
  while random_loc == target_loc:
    random_loc = random.choice(locations)
  goto_loc(random_loc)
```

The landmark resolution prompt is as follows,

```
# Python parsing phrases to locations script

locations = [‘bookshelf’, ‘desk A’, ‘table’, ‘desk B’, ‘doorway’, ‘kitchen counter’, ‘couch’, ‘door’]
semantic_info = {
  “bookshelf”: {“material”: “wood”, “color”: “brown”},
  “desk A”: {“material”: “wood”, “color”: “brown”},
  “desk B”: {“material”: “metal”, ‘color’: “white”},
  “doorway”: {},
  “kitchen counter”: {“color”: “white”},
  “couch”: {“color”: “blue”, “brand”: “IKEA”},
  “door”: {“material”: “steel”, “color”: “grey”},
  “table”: {“color”: “white”},
  }
# wooden brown bookshelf
ret_val = ‘bookshelf’

...

locations = [‘bookshelf’, ‘desk A’, ‘table’, ‘desk B’, ‘doorway’, ‘kitchen counter’, ‘couch’, ‘door’]
semantic_info = {
  “bookshelf”: {“material”: “wood”, “color”: “brown”},
  “desk A”: {“material”: “wood”, “color”: “brown”},
  “desk B”: {“material”: “metal”, ‘color’: “white”},
  “doorway”: {},
  “kitchen counter”: {“color”: “white”},
  “couch”: {“color”: “blue”, “brand”: “IKEA”},
  “door”: {“material”: “steel”, “color”: “grey”},
  “table”: {“color”: “white”},
  }
# blue IKEA couch
ret_val = ‘couch’
```

7 Implementation Details about Grounded Translation

7.1 CopyNet

For reproducing [3], we trained the CopyNet baseline with our grounded dataset preprocessed as its required format. To make a fair comparison on generalization ability, the CopyNet model has only seen utterance-formula pairs from the Boston subset, and the evaluation is run on grounded datasets of the rest 21 cities. For training CopyNet, we followed closely the instructions of the original paper and used the exact same LSTM model structure and pre-computed glove embedding for landmark resolution. On the hyperparameters, we set the embedding size to 128, the hidden size to 256, the learning rate to 10^{-3}, and the batch size to 100.

7.2 Prompt GPT-4

The prompt for end-to-end GPT-4 is as follows. While we tried including a landmark list in the prompt, it was removed in the final version because we observed empirically that Prompt GPT-

Table 1: Dataset Comparison

	Lang2LTL Lifted	CleanUp World	NL2TL	Wang et al. [4]
Number of datapoints	49,655	3,382	39,367	6,556
Unique formula skeletons	47	4	605	45
#Propositions (min, max, mean)	(1, 5, 3.79)	(1, 3, 1.85)	(1, 7, 2.86)	(1, 4, 2.01)
Formula Length (min, max, mean)	(2, 67, 18.89)	(2, 7, 4.77)	(1, 13, 5.98)	(3, 7, 4.48)

4 achieved better performance without explicitly giving a list of landmarks during prompt engineering.

```
Your task is to first find referred landmarks from a given list then use them as propositions to translate
English utterances to linear temporal logic (LTL) formulas.

Utterance: visit Panera Bread sandwich fast food on Stuart Street
LTL: F panera_bread

Utterance: eventually reach Wang Theater, and The Kensington apartments
LTL: & F wang_theater F the_kensington

...

Utterance: make sure that you have exactly three separate visits to Seybolt Park
LTL: M & seybolt_park F & ! seybolt_park F & seybolt_park F & ! seybolt_park F seybolt_park | ! seybolt_park G | seybolt_park G | ! seybolt_park G | seybolt_park G | ! seybolt_park G | seybolt_park G ! seybolt_park

Utterance:
```

8 Dataset Details

8.1 Quantifying diversity of temporal commands

We quantify the diversity of the temporal commands a system is tested on using the temporal formula skeletons in the evaluation corpus of commands. We propose that each novel dataset should be characterized along the following dimensions, and as an example, we provide the respective values for the Lang2LTL dataset (lifted and grounded OSM dataset) described in Section 6.4 of the main paper.

1. Number of semantically unique formulas: 47
2. Number of propositions per formula: minimum: 1, maximum: 5, average: 3.79
3. Length of formulas: minimum: 2, maximum: 67. average: 18.89
4. Vocabulary size (for grounded datasets): 1757
5. Linguistic diversity of utterances: self-BLEU score: 0.85

Table 1 compares our proposed lifted dataset and other datasets proposed in prior work.

9 Detailed Result Analysis on Lifted Translation

We further analyzed the results for each model and holdout type for the lifted translation problem. In particular, we computed the accuracies per each formula type and the number of unique propositions required to construct the target formula. This analysis provides insights into the sensitivity of the models to particular templates and formula lengths.

The accuracies of each model and holdout type categorized by formula types are depicted in Figure 1. We observe that for both the finetuned models (Finetuned T5 and Finetuned GPT-3), the model

achieves high accuracies across various formula types for *Utterance Holdout*. Note that the performance across types is more uniform for the Finetuned GPT-3 than the Finetuned T5-Base model. Next, we note that Prompt GPT-4 achieves better accuracies as compared to Prompt GPT-3 across all evaluations.

We observe that the performance of the finetuned models is more unbalanced across different formula types for the *Formula Holdout* test case. In comparison, Prompt GPT models achieve non-zero accuracies across all formula types. Once again, Prompt GPT-4 outperforms Prompt GPT-3. We note that adding type-constrained decoding to Finetuned T5-Base during inference only marginally improved *Utterance Holdout*, but significantly improved *Formula* and *Type Holdout*, which implies Finetuned T5-Base model is more likely to produce syntactically incorrect output when the grounding formula instance or type have not seen during training.

Finally, we note that only the prompt GPT models achieve meaningful accuracies in the *Type Holdout* scenarios. However, even in *Type Holdout*, the accuracies are concentrated on formula types that only had short lengths or shared subformulas with types seen during training. We can conclude that *Formula* and *Type Holdout* remain challenging paradigms of generation and an open problem for automated translation of language commands into formal specifications.

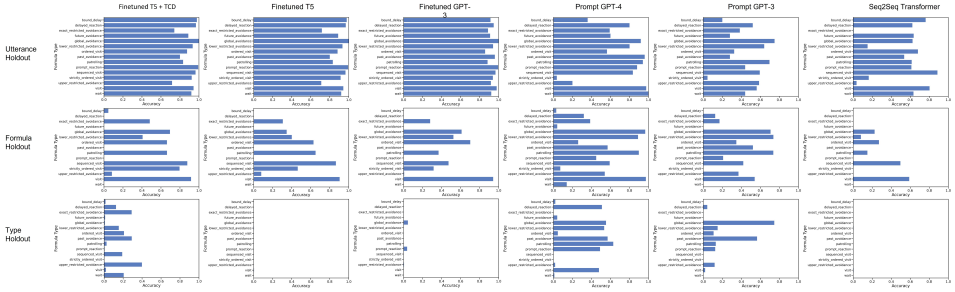


Figure 1: The accuracies per grounding formula types of six lifted translation models

Next, we repeated the above analysis but categorized accuracies by the number of unique propositions that appear within a formula. The results are depicted in Figure 2.

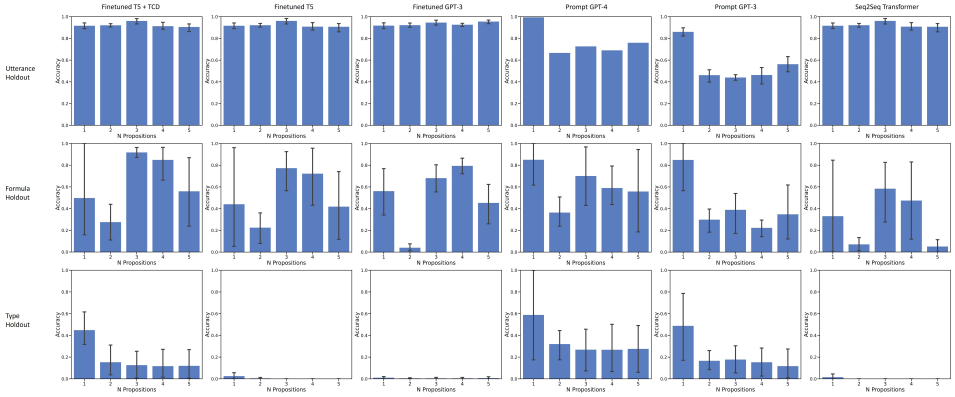


Figure 2: The accuracies per number of unique propositions of six lifted translation models

Here we note that in the *Utterance Holdout* test, the finetuned models demonstrated balanced performance across the dataset, whereas both prompt GPT models demonstrated degraded performance when the number of unique propositions in the formula was increasing. Subsequently, the degraded performance on longer formulas was apparent even within the *Formula* and *Type holdout* domains. In contrast, the three finetuned models performed better for longer formulas in *Formula Holdout*. We hypothesize that this is because the finetuned models were more able to generalize to different formula lengths of the same template (in particular, the templates that required temporal ordering

constraints to be encoded) as compared to the prompt completion-based approaches. In addition, there are more samples in the training set for longer formulas due to permutations of propositions.

As finetuning an LLM on the target task produced the best results for *Utterance Holdout*, we further analyzed the cause of errors for the instances where the lifted translation was incorrect. We categorize the errors as follows:

1. **Syntax Errors:** The formula returned by the lifted translation module was not a valid LTL formula.
2. **Misclassifed formula type:** The lifted translation module returns an identifiable but incorrect formula type that did not correspond to the input command.
3. **Incorrect propositions:** The returned formula was of the correct formula type but had the incorrect number of propositions.
4. **Incorrect permutation:** The formula was of the correct template class and had the right number of propositions, but the propositions were in the wrong location within the formula.
5. **Unknown template** The returned formula was a valid LTL formula but did not belong to any known formula types.

Figure 3 to Figure 5 depict the relative frequencies of the error cases as a pie chart for the three finetuned models. Note that returning unknown formula templates with the correct syntax was the most common cause of error in the lifted translation based on all finetuned models.

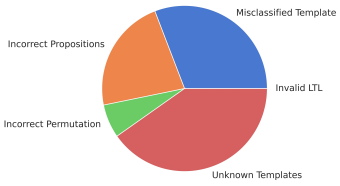


Figure 3: Error frequencies of Finetuned T5-Base with TCD

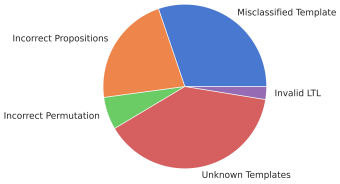


Figure 4: Error frequencies of Finetuned T5-Base

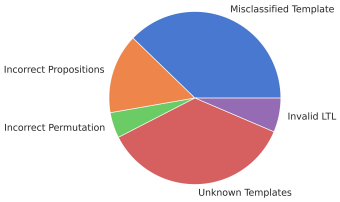


Figure 5: Error frequencies of Finetuned GPT-3

Since Finetuned GPT-3 achieves the best generalization across formula types, and type-constrained decoding (TCD) during inference significantly improves the translation accuracies for unseen formula instances and types, the combination of large language models and TCD is by far the best approach for grounding language commands for temporal tasks.

10 Robot Demonstration

10.1 Indoor Environment #1

The semantic information of landmarks in the first household environment is as follows,


```
{
    "bookshelf": {
        "material": "wood",
        "color": "brown"
    },
    "desk A":{
        "material": "wood",
        "color": "brown"
    },
    "desk B": {
        "material": "metal",
        "color": "white"
    },
```

```
    "doorway": {},
    "kitchen counter": {
        "color": "white"
    },
    "couch": {
        "color": "blue",
        "brand": "IKEA"
    },
    "door": {
        "material": "steel",
        "color": "grey"
    },
    "table": {
        "color": "white"
    }
}
```

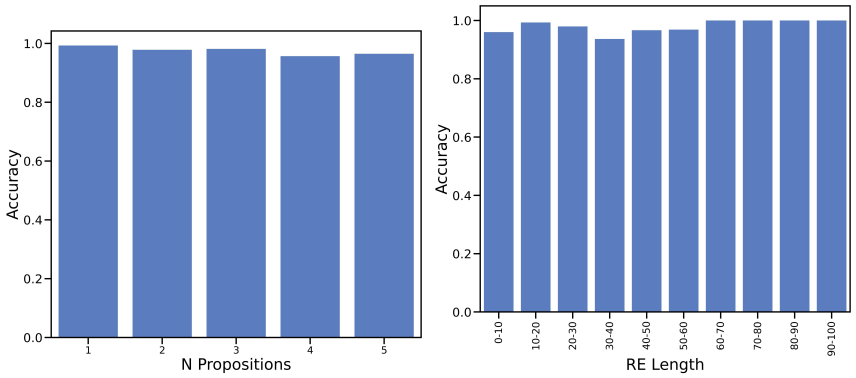
Natural language commands used to test our system Lang2LTL and Code as Polices [5] are shown in Table 2.

10.2 Indoor Environment #2

The semantic information of landmarks in the second household environment is as follows,

```
{
    "hallway A": {
        "decoration": "painting"
    },
    "hallway B": {
        "decoration": "none"
    },
    "table A": {
        "location": "kitchen",
        "material": "metal",
        "color": "blue"
    },
    "table B": {
        "location": "atrium",
        "material": "metal",
        "color": "white"
    },
    "classroom": {
        "door": ["glass", "grey"]
    },
    "elevator": {
        "color": "purple"
    },
    "staircase": {},
    "front desk": {},
    "office": {
        "door": ["wood", "yellow"]
    },
}
```

Natural language commands used to test our system Lang2LTL and Code as Polices [5] are shown in Table 3.



(a) RER Accuracy vs. Command Complexity (b) REG Accuracy vs. RE Complexity

Figure 6: Figure 6a shows the accuracies of the referring expression recognition (RER) module as the complexity of commands (measured by the number of referring expressions in the command) increases. Figure 6b shows the accuracy of the referring expression grounding (REG) module as the complexity of REs (measured by string length) increases.

References

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Table 2: Commands for Robot Demonstration in Indoor Environment #1

Navigational Command	Lang2LTL Result	Code as Policies Result
1. go to brown bookshelf, metal desk, wooden desk, kitchen counter, and the blue couch in any order	success	success
2. move to grey door, then bookrack, then brown desk, then counter, then white desk	success	success
3. visit brown wooden desk but only after bookshelf	success	misunderstand the task
4. go from brown bookshelf to white metal desk and only visit each landmark one time	success	misunderstand the task
5. go to brown wooden desk exactly once and do not visit brown desk before bookshelf	success	inexecutable
6. go to white desk at least three times	success	inexecutable
7. go to wooden bookshelf at least five times	success	success
8. visit bookshelf at most three times	success	success
9. visit counter at most 5 times	success	success
10. go to wooden desk exactly three times	success	misunderstand the task
11. move to brown wooden desk exactly 5 times	success	inexecutable
12. go to doorway exactly two times, in addition always avoid the table	success	success
13. go to brown desk only after visiting bookshelf, in addition go to brown desk only after visiting white desk	success	misunderstand the task
14. visit wooden desk exactly two times, in addition do not go to wooden desk before bookrack	success	inexecutable
15. visit wooden desk at least two times, in addition do not go to wooden desk before bookshelf	success	inexecutable
16. visit the blue IKEA couch, in addition never go to the big steel door	success	success
17. visit white kitchen counter then go to brown desk, in addition never visit white table	success	success
18. go to the grey door, and only then go to the bookshelf, in addition always avoid the table	success	misunderstand the task
19. go to kitchen counter then wooden desk, in addition after going to counter, you must avoid white table	success	misunderstand the task
20. Go to bookshelf, alternatively go to metal desk	success	misunderstand the task
21. Go to counter, alternatively go to metal desk	success	misunderstand the task
22. Go to the counter, but never visit the counter	unsatisfiable. abort correctly	stop execution correctly
23. do not go to the wooden desk until bookshelf, and do not go to bookshelf until wooden desk	unsatisfiable. abort correctly	stop execution correctly
24. go to brown desk exactly once, in addition go to brown desk at least twice	unsatisfiable. abort correctly	misunderstand the task
25. find the kitchen counter, in addition avoid the doorway	unsatisfiable. abort correctly	stop execution correctly
26. move to couch exactly twice, in addition pass by counter at most once	unsatisfiable. abort correctly	stop execution correctly
27. navigate to the counter then the brown desk, in addition after going to the counter, you must avoid doorway	unsatisfiable. abort correctly	misunderstand the task
28. Visit the counter at least 2 times and at most 5 times	incorrect grounding. OOD	inexecutable
29. visit counter at least six times	incorrect grounding. OOD	success
30. either go to bookshelf then desk A, or go to couch	incorrect grounding. OOD	misunderstand the task

Table 3: Commands for Robot Demonstration in Indoor Environment #2

Navigational Command	Lang2LTL Result	Code as Policies Result
1. navigate to the office with the wooden door, the classroom with glass door and the table in the atrium, kitchen counter, and the blue couch in any order	success	success
2. go down the hallway decorated with paintings, then find the kitchen table, then front desk, then staircase	success	success
3. navigate to classroom but do not visit classroom before the white table in atrium	success	misunderstand the task
4. only visit classroom once, and do not visit classroom until you visit elevator first	success	success
5. Go to the staircase, front desk and the white table in the atrium in that exact order. You are not permitted to revisit any of these locations	success	inexecutable
6. go to the purple elevator at least five times	success	inexecutable
7. visit the kitchen table at most three times	success	success
8. navigate to the classroom exactly four times	success	inexecutable
9. go to the front desk then the yellow office door, in addition do not visit the classroom with glass door	success	success
10. go to the stairs then the front desk, in addition avoid purple elevator	success	success
11. move to elevator then front desk, in addition avoid staircase	success	success
12. go to front desk exactly two times, in addition avoid elevator	success	inexecutable
13. Go to elevator, alternatively go to staircase	success	misunderstand the task
14. Go to the front desk at least two different occasions, in addition you are only permitted to visit the staircase at most once	success	misunderstand the task
15. Visit the elevator exactly once, in addition visit the front desk on at least 2 separate occasions	success	inexecutable
16. Go to the office, in addition avoid visiting the elevator and the classroom	success	success
17. Visit the front desk, in addition you are not permitted to visit elevator and staircase	success	success
18. Visit the purple door elevator, then go to the front desk and then go to the kitchen table, in addition you can never go to the elevator once you've seen the front desk	success	inexecutable
19. Visit the front desk then the white table, in addition if you visit the staircase you must avoid the elevator after that	success	inexecutable
20. Go to the classroom with glass door, but never visit the classroom with glass door	unsatisfiable. abort correctly	stop execution correctly
21. do not go to the white table until classroom, and do not go to the classroom until white table	unsatisfiable. abort correctly	stop execution correctly
22. go to kitchen table exactly once, in addition go to kitchen table at least twice	unsatisfiable. abort correctly	misunderstand the task
23. find the office, in addition avoid visiting the front desk and the classroom and the table in atrium	unsatisfiable. abort correctly	stop execution correctly
24. move to the kitchen table exactly twice, in addition pass by hallway decorated by paintings at most once	unsatisfiable. abort correctly	misunderstand the task
25. navigate to the kitchen table then the front desk, in addition after going to the kitchen table, you must avoid hallway decorated with paintings	unsatisfiable. abort correctly	misunderstand the task
26. Go to the front desk at least 4 different occasions, additionally, you are only permitted to visit the staircase at most once	incorrect grounding. OOD	inexecutable
27. Visit the front desk, additionally if you visit the elevator you must visit the office after that	incorrect grounding. OOD	success
28. Visit the front desk, additionally you visit the elevator you must visit the office after that the white table and the classroom	incorrect grounding. OOD	misunderstand the task

Table 4: Specification Patterns for Lang2LTL

Specification Type	Explanation	Formula
Visit	Visit a set of waypoints $\{p_1, p_2 \ldots, p_n\}$ in any order	$\bigwedge_{i=1}^{n} \mathbf{F}\, p_i$
Sequence Visit	Visit a set of waypoints $\{p_1, p_2 \ldots, p_n\}$, but ensure that p_2 is visited at least once after visiting p_1, and so on	$\mathbf{F}(p_1 \wedge \mathbf{F}(p_2 \wedge \ldots \wedge \mathbf{F}(p_n)) \ldots)$
Ordered Visit	Visit a set of waypoints $\{p_1, p_2 \ldots, p_n\}$, but ensure that p_2 is never visited before visiting p_1	$\mathbf{F}(p_n) \wedge \bigwedge_{i=1}^{n-1}(\neg p_{i+1}\, \mathbf{U}\, p_i)$
Strictly Ordered Visit	Visit a set of waypoints $\{p_1, p_2 \ldots, p_n\}$, but ensure that p_2 is never visited before visiting p_1, additionally, ensure that p_1 is only visited on a single distinct visit before completing the rest of the task	$\mathbf{F}(p_n) \wedge \bigwedge_{i=1}^{n-1}(\neg p_{i+1}\, \mathbf{U}\, p_i) \wedge \bigwedge_{i=1}^{n-1}(\neg p_i\, \mathbf{U}\, (p_i\, \mathbf{U}\, (\neg p_i\, \mathbf{U}\, p_{i+1})))$
Patrolling	Visit a set of wwaypoints $\{p_1, p_2 \ldots, p_n\}$ infinitely often	$\bigwedge_{i=1}^{n} \mathbf{GF} p_i$
Bound Delay	If and only if the proposition a is ever observed, then the proposition b must hold at the very next time step	$\mathbf{G}(a \leftrightarrow \mathbf{X}b)$
Delayed Reaction	If the proposition a is ever observed, then its response is to ensure that the proposition b holds at some point in the future	$\mathbf{G}(a \rightarrow \mathbf{F}b)$
Prompt Reaction	If the proposition a is ever observed, then the proposition b must hold at the very next time step	$\mathbf{G}(a \rightarrow \mathbf{X}b)$
Wait	The proposition a must hold till the proposition b becomes true, and b may never hold	$a\ \mathbf{W}\ b$
Past Avoidance	The proposition a must not become true until the proposition b holds first. b may never hold	$\neg a\ \mathbf{W}\ b$
Future Avoidance	Once the proposition a is observed to be true, the proposition b must never be allowed to become true from that point onwards.	$\mathbf{G}(a \rightarrow \mathbf{XG}\neg b)$
Global Avoidance	The set of propositions $\{p_1, p_2 \ldots, p_n\}$ must never be allowed to become true	$\bigwedge_{i=1}^{n} \mathbf{G}(\neg p_i)$
Upper Restricted Avoidance	The waypoint a can be visited on at most n separate visits	For $n = 1$, $\neg\mathbf{F}(a \wedge (a\, \mathbf{U}\, (\neg a \wedge (\neg a\, U\, \mathbf{F}a))))$ For $n = 2$, $\neg\mathbf{F}(a \wedge (a\ U\ (a \wedge (\neg a\, \mathbf{U}\, \mathbf{F}(a \wedge (a\, \mathbf{U}\, (\neg a \wedge (\neg a\, \mathbf{U}\, Fa))))))))$
Lower Restricted Avoidance	The waypoint a must be visited on at least n separate visits	For $n = 1$, $\neg\mathbf{F}a$ for $n = 2$, $\mathbf{F}(a \wedge (a\, \mathbf{U}\, (\neg a \wedge (\neg a\, U\, \mathbf{F}a))))$
Exact Restricted Avoidance	The waypoint a must be visited on exactly n separate visits	For $n = 1$, $a\, \mathbf{M}\, (\neg a \vee \mathbf{G}(a \vee \mathbf{G}\neg a))$ For $n = 2$, $(a \wedge \mathbf{F}(\neg a \wedge \mathbf{F}a))\mathbf{M}(\neg a \vee \mathbf{G}(a \vee \mathbf{G}(\neg a \vee \mathbf{G}(a \vee \mathbf{G}\neg a))))$

Table 5: Example Commands from OpenStreetMap Dataset

LTL Type	Command (with two referring expressions)
Visit	move to Thai hot pot restaurant on Kneeland Street, and Vietnamese restaurant on Washington Street
Sequence Visit	visit Subway sandwich shop on The Plaza, followed by Zada Jane's Cafe on Central Avenue
Ordered Visit	find Local Goods Chicago gift shop, but not until you find Currency exchange bureau, first
Strictly Ordered Visit	reach Citibank branch, and then Cutler Majestic Theater on Tremont Street, in that exact order without repetitions
Patrolling	keep on visiting US Post Office on West Devon Avenue, and Kanellos Shoe Repair shop
Bound Delay	you must go to Purple Lot parking area, immediately after you visit Royal Nails & Spa on South Main Street, and you can not go to Purple Lot parking area, any other time
Delayed Reaction	you must visit Peruvian restaurant on Virginia Avenue, once you visit PNC Bank
Prompt Reaction	immediately after you go to Beachside Resortwear clothing store, you must go to Walgreens Pharmacy
Wait	you can not go to other place from Publix supermarket, unless you see Beaches Museum
Past Avoidance	avoid visiting IES Test Prep school, till you observe bookstore on Elizabeth Street
Future Avoidance	never go to Commercial building on 5th Avenue, once you go to Cafe Metro
Global Avoidance	make sure to never reach either Citibank, or Seybolt Park
Upper Restricted Avoidance	go to Cocktail bar, at most twice
Lower Restricted Avoidance	you have to visit Main Branch of CoGo Bike Share Library for bicycle rental, two or more than two times
Exact Restricted Avoidance	navigate to Art shop on Bannock Street, exactly twice

Table 6: Results of Recognizing Referring Expression with Spatial Relations

Navigational Command	Referring Expression(s)	Correctness
1. go to back of Common Market	back of Common Market	correct
2. always avoid entrance and exit of Little Sugar Creek, but visit left and right of Little Sugar Creek	entrance and exit of Little Sugar Creek | left and right of Little Sugar Creek	correct
3. stay at intersection of Thayer street and Waterman street	intersection of Thayer street and Waterman street	correct
4. move forward to the south of Edgebrook Coffee Ship	south of Edgebrook Coffee Ship	correct
5. go to east of Chinatown, without visiting west of New Saigon Sandwich, then go to front of New Saigon Sandwich, without visiting rear of Dumpling Cafe, then go to rear of Dumpling Cafe, without visiting north of Emerson College - Little Building, finally go to south Emerson College - Little Building, while only visiting each location once	east of Chinatown | west of New Saigon Sandwich | front of New Saigon Sandwich — rear of Dumpling Cafe | rear of Dumpling Cafe | north of Emerson College - Little Building | south Emerson College - Little Building	correct
6. go around big blue box	big blue box	incorrect
7. go to exit of blue area through between red room and blue one	exit of blue area | red room | blue one	incorrect
8. go to left of CVS and the stay on bridge	left of CVS | bridge	incorrect
9. go pass right of Dairy Queen to left of Harris Teeter, end up at entrance of Wells Fargo	Dairy Queen | Harris Teeter | Wells Fargo	incorrect
10. move to My Sister's Closet and stop close to bus stop near Ace Hardware	My Sister's Closet | bus stop near Ace Hardware	incorrect