Generating Open-World & Multi-Hierarchy Scene Graphs for Human-Instructed Manipulation Tasks via Foundation Models

Sandeep S. Zachariah*, Aman Tambi*, Moksh Malhotra, P. V. M. Rao and Rohan Paul
Indian Institute of Technology Delhi

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Motivation and Challenges

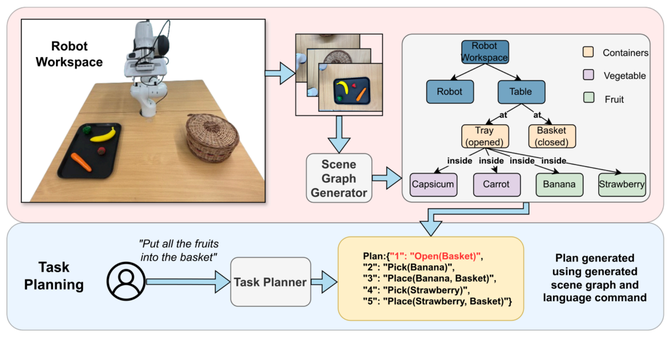
Consider a robot asked to "*bring me all the fruits*" or "*put the book which has spectacles on top of it on the rack*". Following such instructions requires the robot to possess:

- grounded semantic understanding of its environment in terms of which objects are present,
- metric location and extent of objects and,
- how objects are related to each other (inside, left of, behind, supported by etc.).

Method	Objects		Relations		
	Detection	Pose	Spatio-depth	Planar	Abstraction
GPT-4V	✓	✗	✓	✗	✓
CogVLM	✓	✓	✗	✗	✗
GPT-4V+GDINO	✓	✓	✓	✓	✓
GPT-4V+CogVLM	✓	✓	✓	✓	✓
ConceptGraph	✓	✓	✓	✗	✗
Proposed	✓	✓	✓	✓	✓

Approaches like ***Hydra***[1] use supervised learning methods to infer metric-semantic graph representations for a scene - fails for open-world settings.

Concept-Graphs[2] generates scene graphs for open-world settings but is not amenable to rapid update necessary for task execution in dynamic scenes.



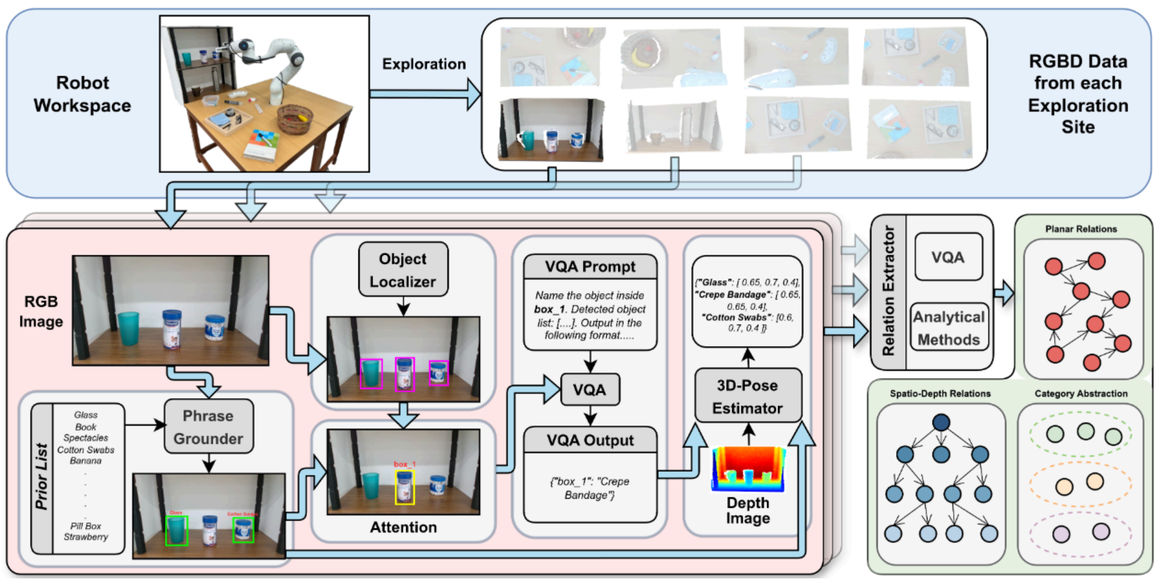
Need of a scene graph for abstract instruction following.

Technical Approach

We employ a factored approach for graph generation as (i) detecting presence and the type of objects and (ii) estimating inter-object relations.

$$\text{ObjectDetection}(\mathcal{I}_{o:T}) \rightarrow \mathcal{O} \qquad \text{RelationEstimation}(\mathcal{I}_{o:T}|\mathcal{O}) \rightarrow \mathcal{R}$$

Scene Graph Generation Pipeline



Problem Setup

The robot is operating in an environment populated by **a-priori** set of objects $o \in O$. The robot's overall task is to synthesize the sequence of actions $\pi = [a_0, a_1, .. a_n]$ in response to the natural language command $\lambda \in \Lambda$.

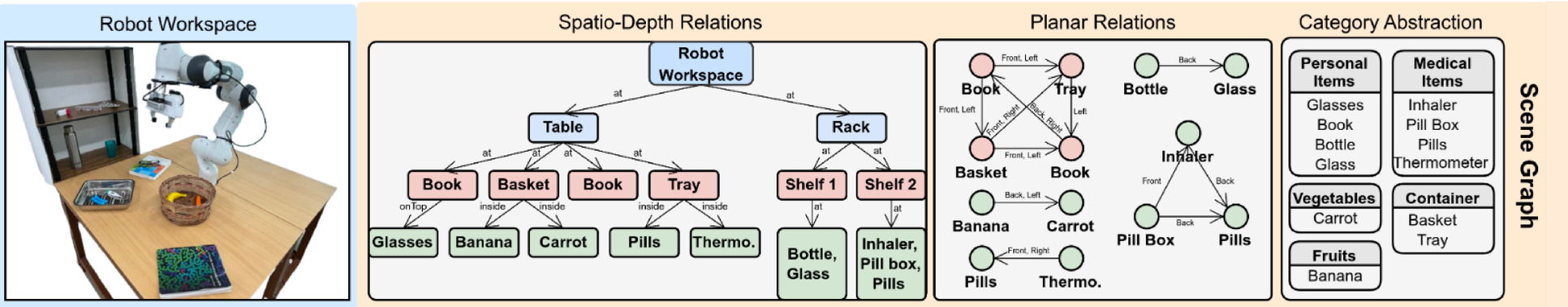
In order to generate π the robot must infer a scene graph G_t that models objects O and relations R at time t from a sequence of RGB-D information $I_{o:T}$ captured by the robot.

$$\text{SceneGraphGeneration}(\mathcal{I}_{o:T}) \rightarrow \mathcal{G}_T = (\mathcal{O}, \mathcal{R})$$

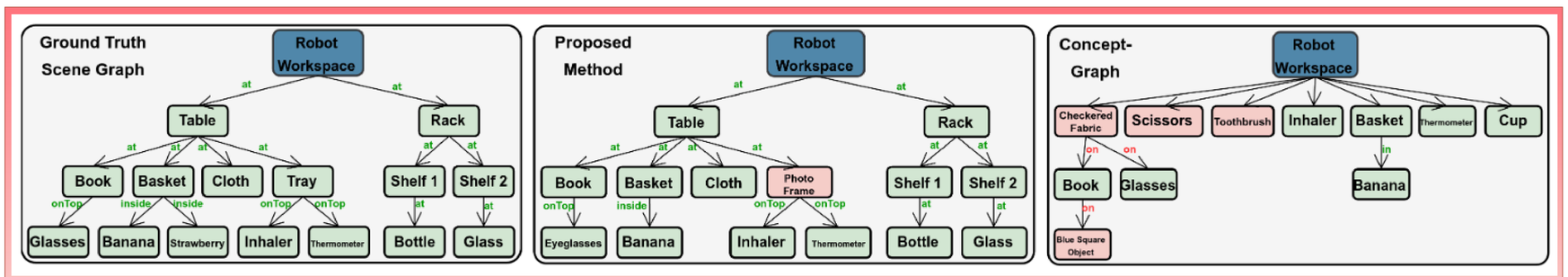
Modeling Objects : A combination of a **grounding model and a Visual Question Answering (VQA) model** is employed to detect objects. Attention is provided to these VQA models in the form of unlabelled bounding boxes, masks, or cropped images.

Modeling Relations: Spatio-depth relations ("onTop", "inside", "at"), category abstractions ("fruits", "medicinal items"), planar relations ("left", "front").
For extracting spatio-depth relations and category abstractions, a VQA model (GPT-4V) is used and planar relations are calculated analytically.

Results



Multi-hierarchical Scene Graphs: The figure shows the scene and the corresponding multi-hierarchical scene graph that was generated for the given robot workspace.

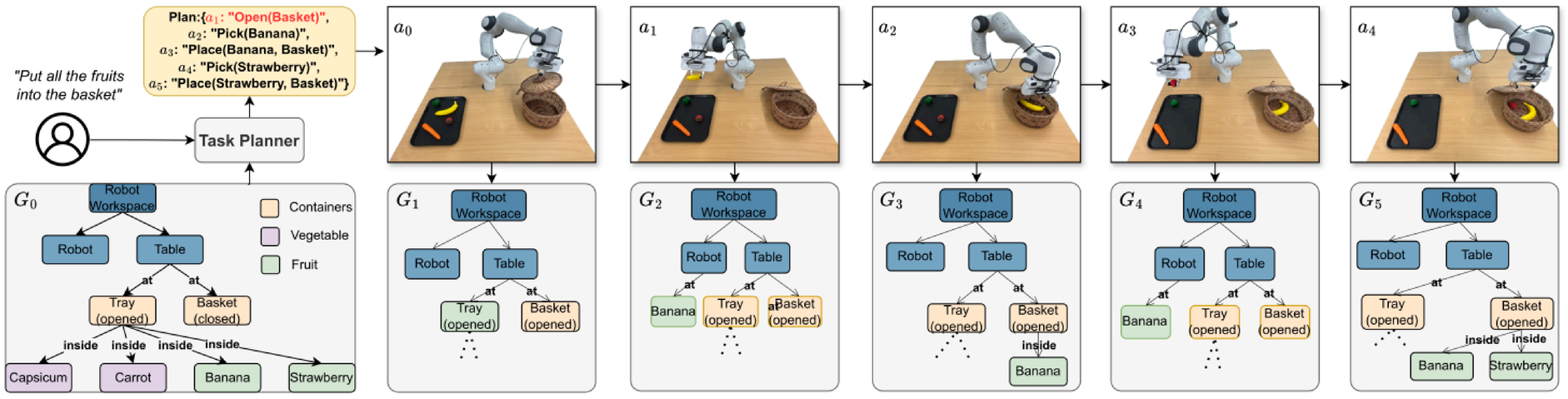


Qualitative Comparison of Scene Graphs: Proposed Method vs Concept-Graphs. The proposed method generates a scene graph closer to the ground truth. Results indicate that reliable relation extraction is dependent on object detection accuracy.

Method	Precision (%)	Recall (%)	F-measure
GDino+GPT-4V	85.0	57.0	0.68
CogVLM+GPT-4V	62.1	93.8	0.75
CogVLM	79.5	77.8	0.79
ConceptGraphs	44.8	73.2	0.54
ConceptGraphs-D	55.8	38.7	0.46
Ours	**94**	**96**	**0.95**

Accuracy of object detection. The proposed object detection pipeline has the highest F-measure showing its robustness in open-world settings

Plan Rollout: The figure shows the execution of the plan by the Franka Emika arm in response to the language instruction. The proposed scene graph supports **abstract language instructions**. It also illustrates how the scene graph gets **locally updated** after each action execution.



Conclusion

We introduce a novel approach for generating multi- hierarchical scene graphs for **open-world** settings which facilitates the execution of **sequential and long-horizon plans**. It employs a **factored approach** to scene graph generation, first detecting objects and then establishing relations between them.

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References

[1] N. Hughes, Y. Chang, and L. Carlone. Hydra: A real-time spatial perception system for 3d scene graph construction and optimization. arXiv preprint arXiv:2201.13360, 2022.
[2] Q. Gu, A. Kuwajerwala, S. Morin, K. M. Jatavallabhula, B. Sen,A. Agarwal, C. Rivera, W. Paul, K. Ellis, R. Chellappa, et al. Conceptgraphs: Open-vocabulary 3d scene graphs for perception and planning. arXiv preprint arXiv:2309.16650, 2023.

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