Active Perception using Neural Radiance Field

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Imagine the following search and rescue robot

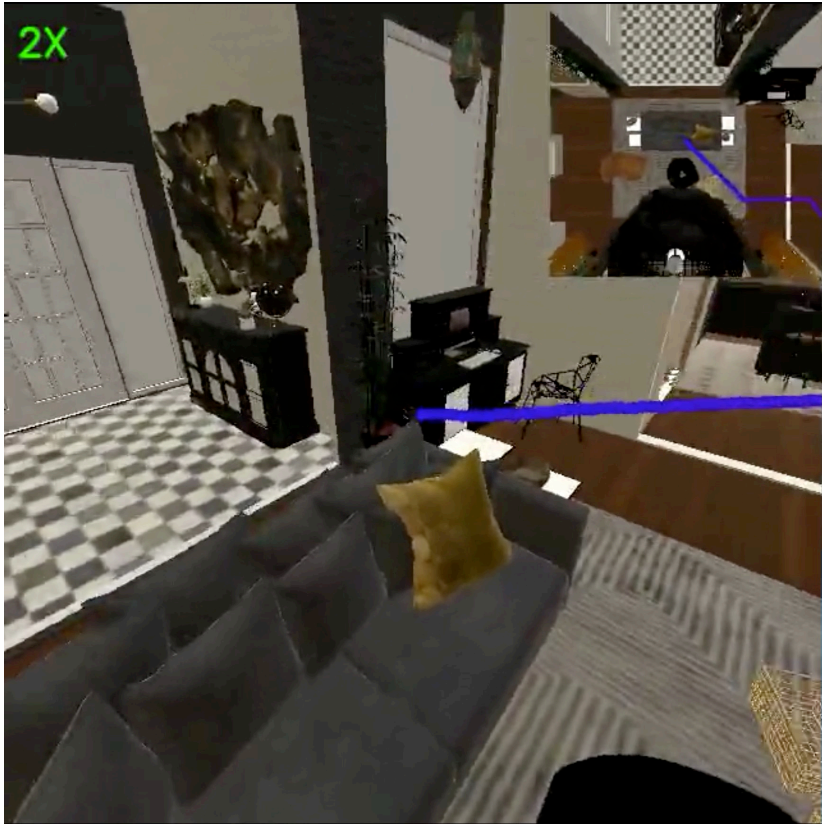
Its mission is to

- Autonomously navigate the challenging environments of damaged buildings after earthquakes.
- Locate survivors and provide data to rescue teams to enhance the effectiveness and safety of their operations.

Active Perception Problem

Intuitively, the robot needs to coarsely explore unseen areas and re-visit them later to learn more details.

To achieve this, we argue that the robot should always go to areas with more information.

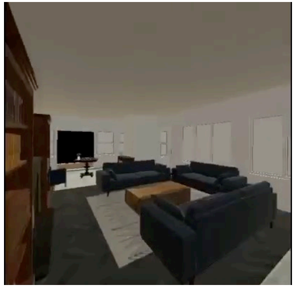


Quantifying Information

Possibilities before (re-)visiting

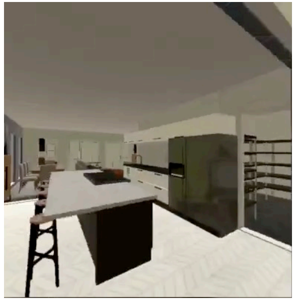
Possibilities after (re-)visiting

Area 1



More Information

Area 2



Less Information

Quantifying Information

Uncertainty in an area is formalized as the entropy $\mathcal{H}(y_{future})$ of possible future observations y_{future}.

Given the new observation y, entropy is reduced to $\mathcal{H}(y_{future}|y)$.

Information gain (mutual information) is the reduction in entropy:

$$\mathcal{H}(y_{future}) - \mathcal{H}(y_{future}|y).$$

Quantifying Information

$$\mathcal{H}(y_{future}) = -\int \log p(y_{future}) dp(y_{future})$$

$$\mathcal{H}(y_{future}|y) = -\int \log p(y_{future}|y) dp(y_{future}|y)$$

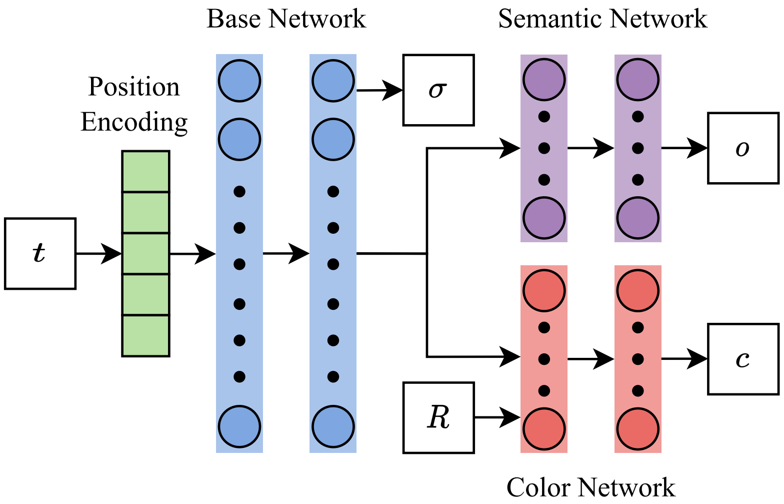
We need a generative model to

a. Estimate $p(y_{future})$

b. Incorporate y and estimate $p(y_{future}|y)$.

Implementation: NeRF

A generative model $p(y_{future})$ is created based on bootstrapped ensemble of semantic neural radiance fields (NeRF).



Semantic NeRF Architecture

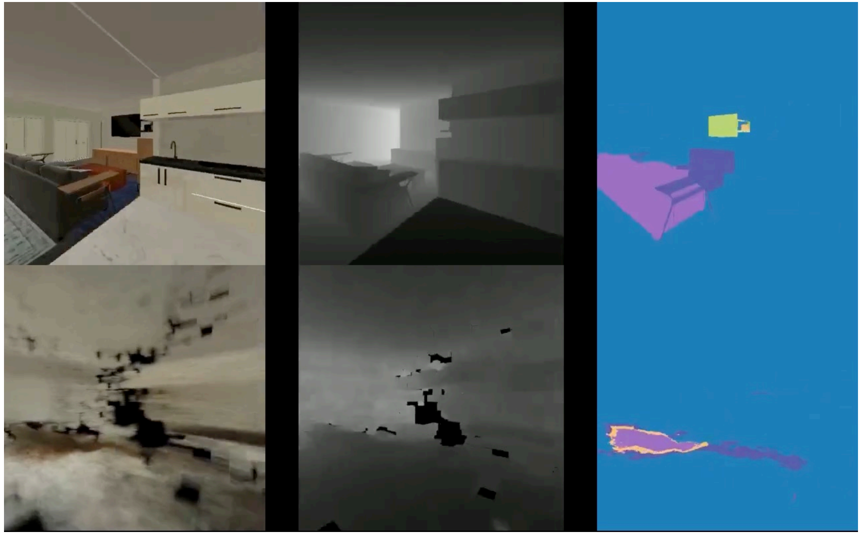
Implementation: NeRF

This model estimates the distribution over future colors, geometries, and object labels.

Color | Geometry | Labels

Actual future observation

Mean of the estimation

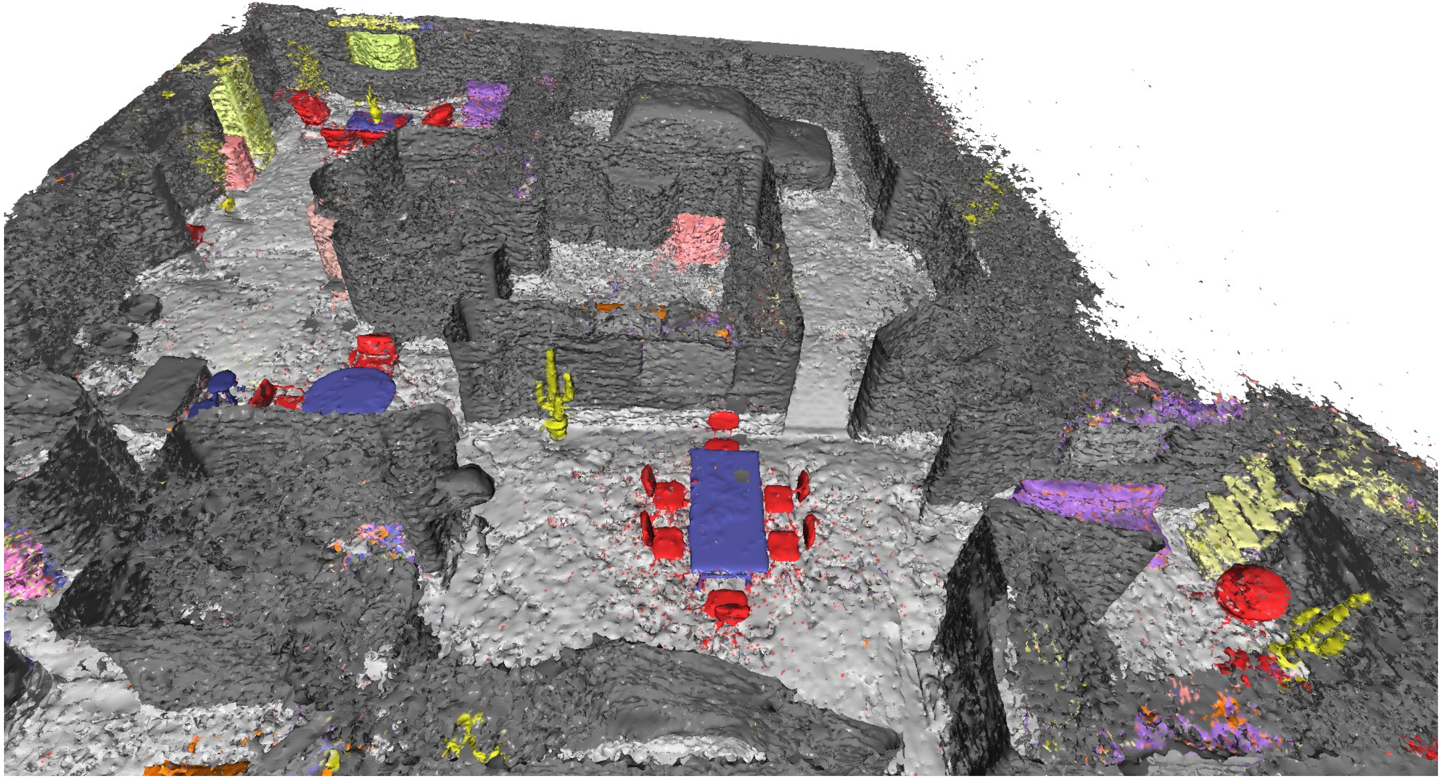


Maximization of Information

The robot needs to select a trajectory u that maximizes the information gain:

$$\arg max_u \mathcal{H}(y_{future}) - \mathcal{H}(y_{future}|y).$$

Results



Conclusions

By maximizing the reduction in entropy, the robot can autonomously explore unseen areas and revisit them later to learn more details.

This formulation can be applied in various scenarios such as search and rescue, planetary exploration, environmental monitoring, and structural inspections.