Deep Semantic Hypothesis-based Planning over Uncertain Point Clouds

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** Equal contribution, random order*

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What makes an outdoor environment challenging for autonomous navigation?

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Not just complicated geometrical structure...

A seemingly simple outdoor environment:

Cass Park in Ithaca NY

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Navigating Challenging Environments

- **Goal:** Safe navigation through unstructured outdoor environments

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Key Insight: It is important to reason about semantics of the environment – terrain and obstacle recognition can improve planned path safety.

DeepSemanticHPPC

Start: Initial Position →

DeepSemanticHPPC

Given initial position in a 3D environment with unknown semantics, plan a safe path to the goal.

DeepSemanticHPPC

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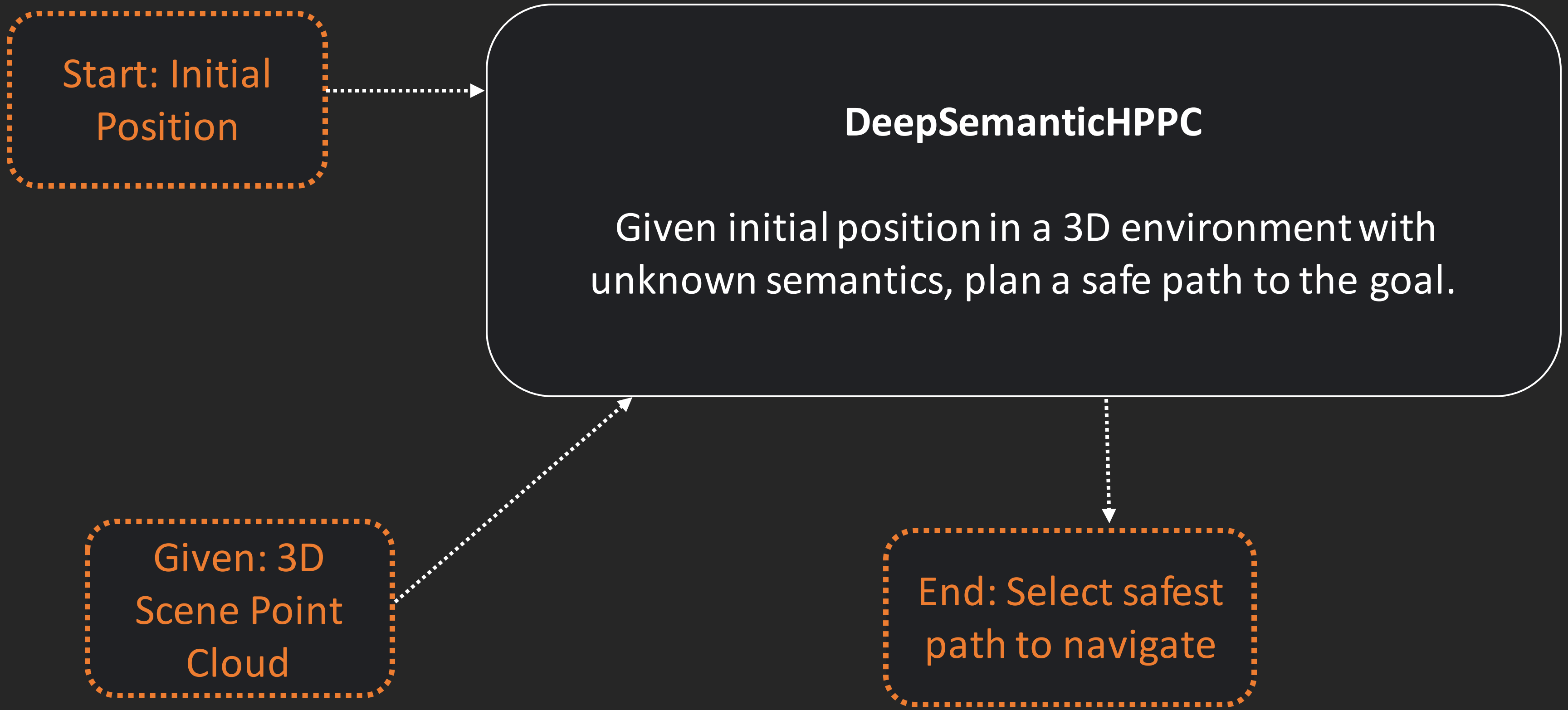
Given: 3D Scene Point Cloud

DeepSemanticHPPC

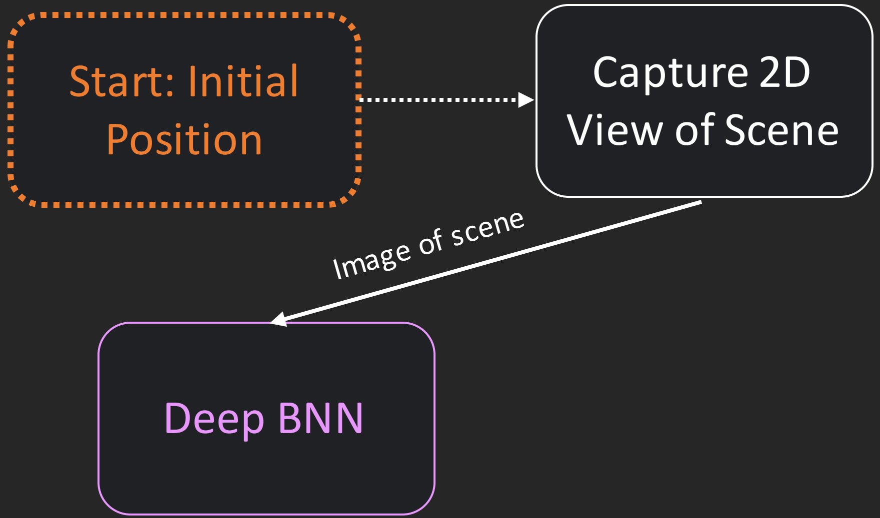


DeepSemanticHPPC

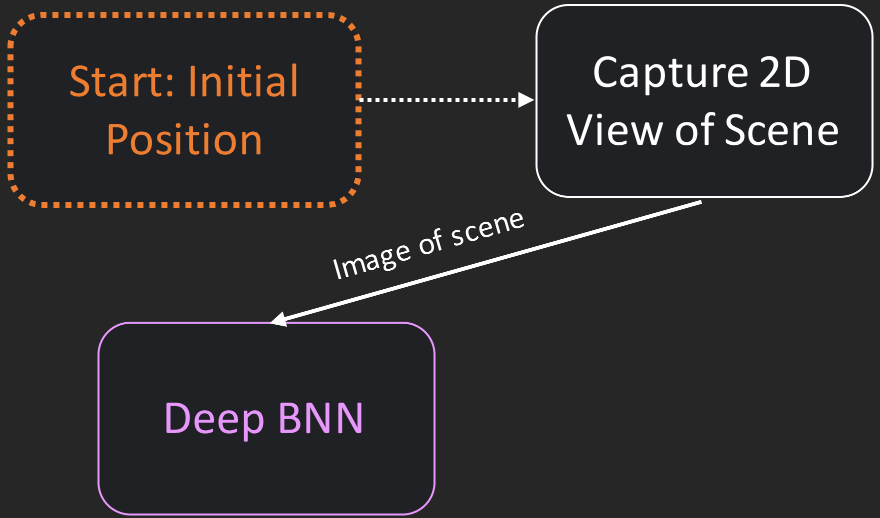
Start: Initial Position

Capture 2D View of Scene

DeepSemanticHPPC



DeepSemanticHPPC

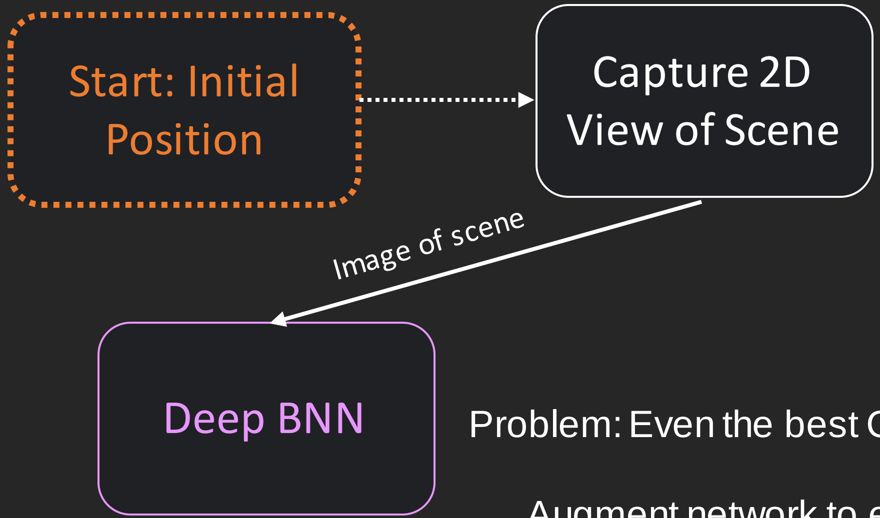


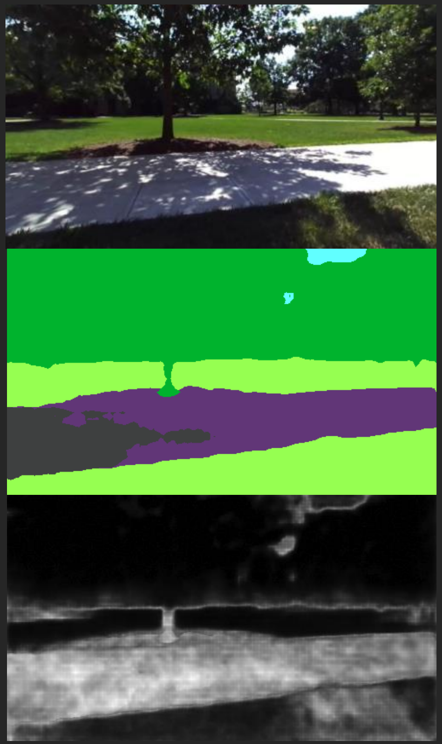
Leverage SOTA image segmentation network (Chen, *et al.* 2018)

Dataset: https://deepsemantichppc.github.io

- Filter unstructured scene categories for COCO
- Consolidate class categories for outdoor recognition

DeepSemanticHPPC

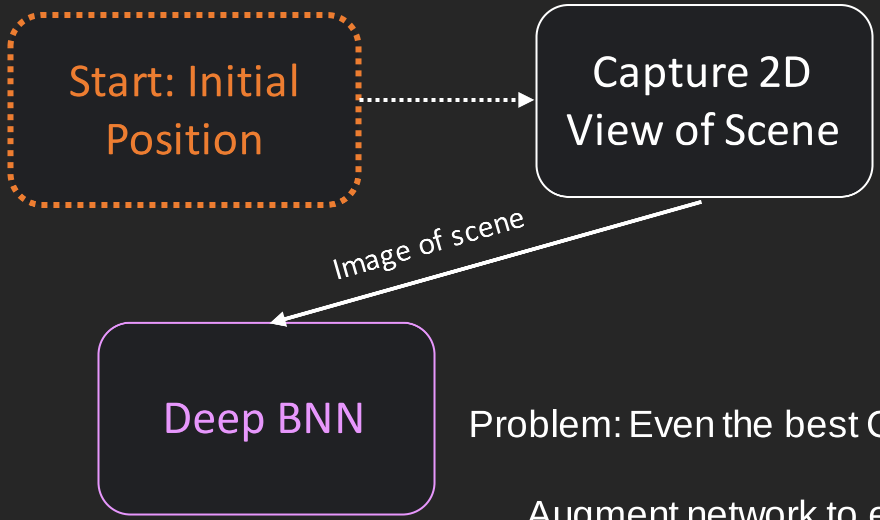




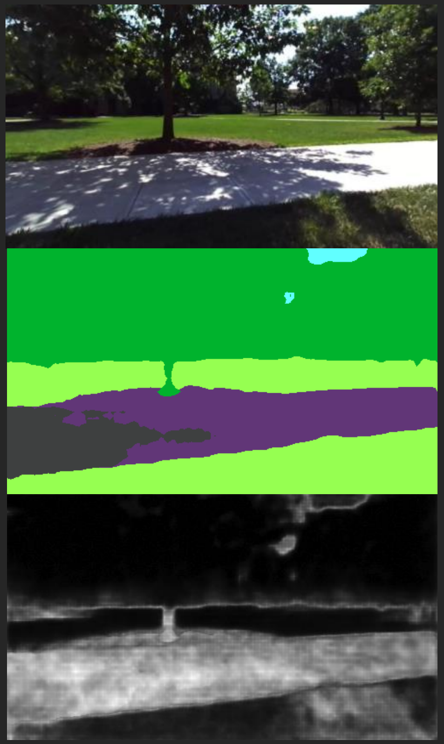
Problem: Even the best CNNs can make mistakes!

Augment network to estimate semantic label uncertainty via Monte Carlo drop out method (Gal, *et al.* 2015)

DeepSemanticHPPC



- Tree
- Pavement
- Grass
- Dirt
- Road



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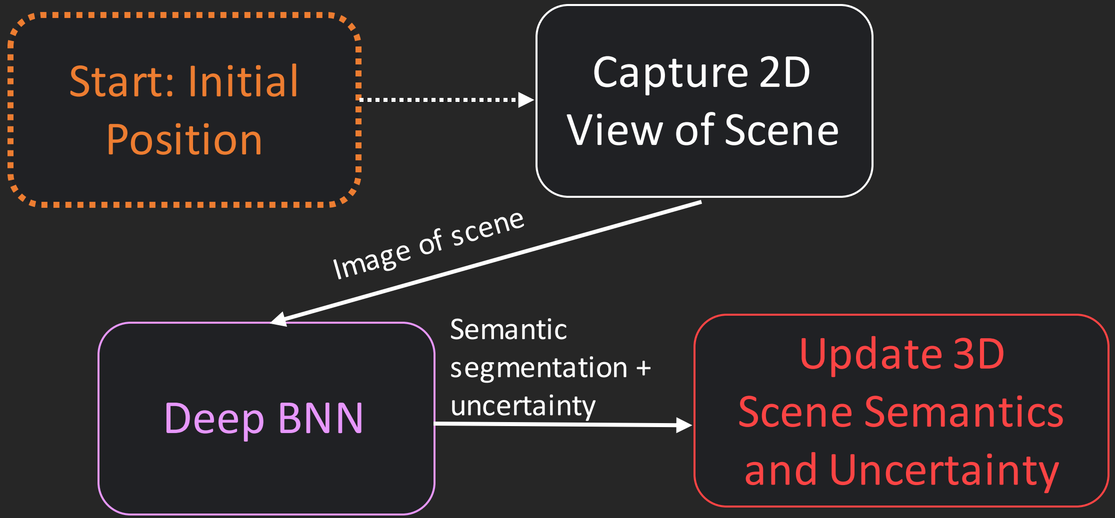
$$\boldsymbol{p}^{(i,j)x} = \frac{1}{T}\sum_{t=1}^{T} s_t^{(i.j)x}\,(y|X) \qquad \boldsymbol{\sigma}^{(i,j)x} = \sqrt{\frac{\sum_{t=1}^{T}(s_t^{(i,j)x}(y|X) - \boldsymbol{p}^{(i.j)x})^2}{T-1}}$$

DeepSemanticHPPC



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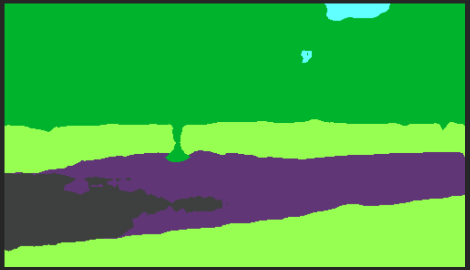
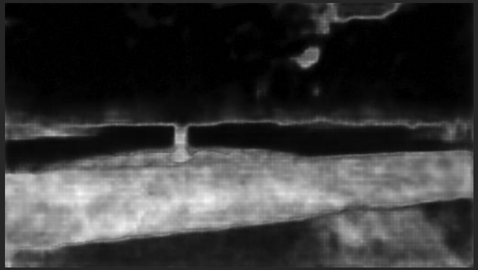
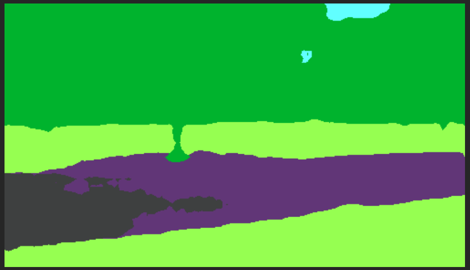
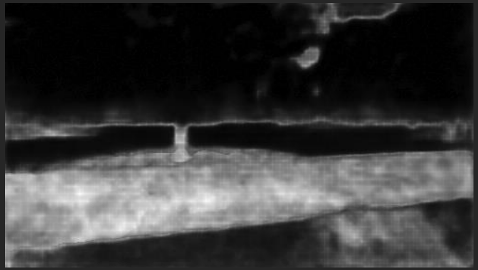


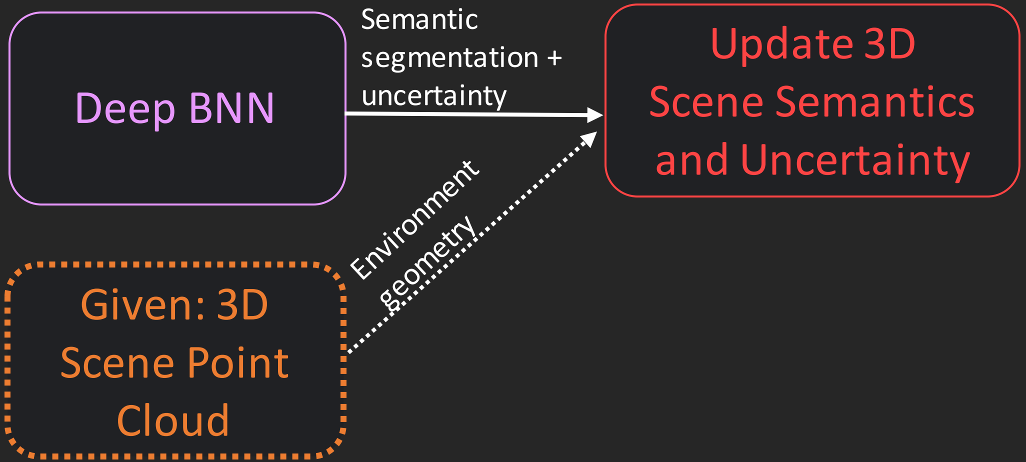


Deep BNN → Semantic segmentation + uncertainty → Update 3D Scene Semantics and Uncertainty

DeepSemanticHPPC







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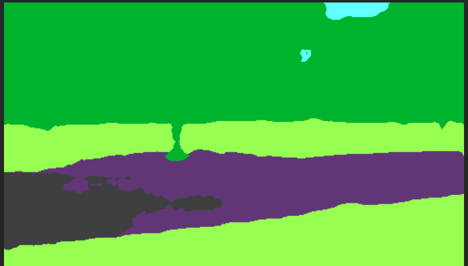
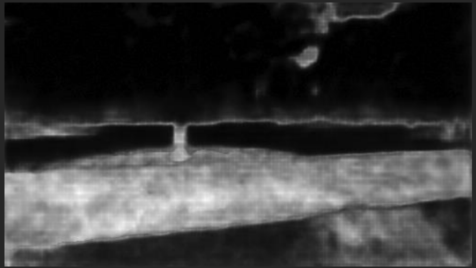




Deep BNN

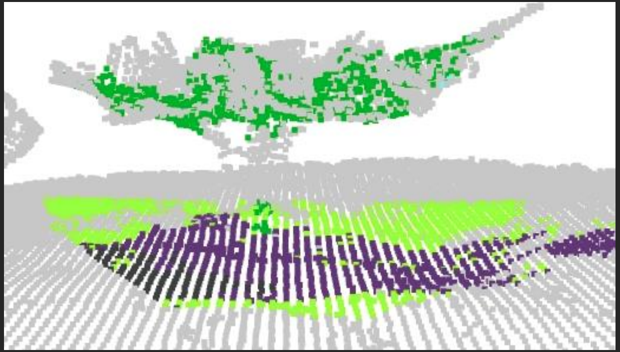
Semantic segmentation + uncertainty

Update 3D Scene Semantics and Uncertainty

Environment geometry

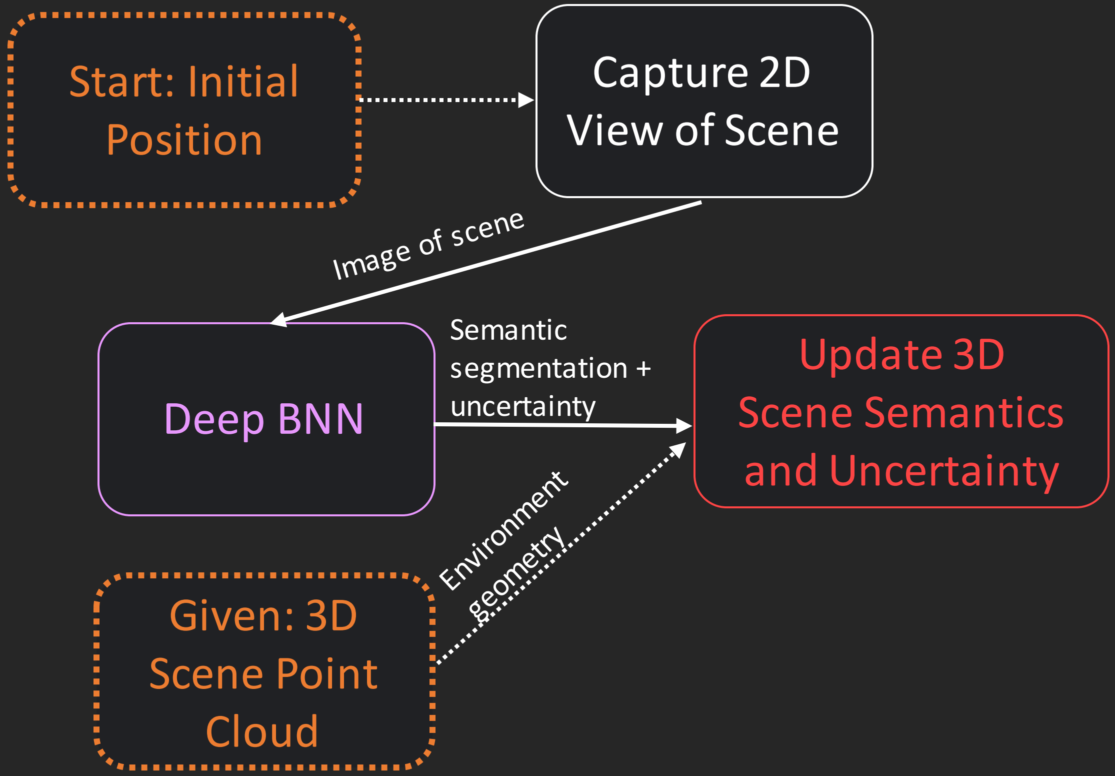
Given: 3D Scene Point Cloud

Environment Point Cloud



Semantic labels for points with uncertainties (uncertainties not shown)

DeepSemanticHPPC



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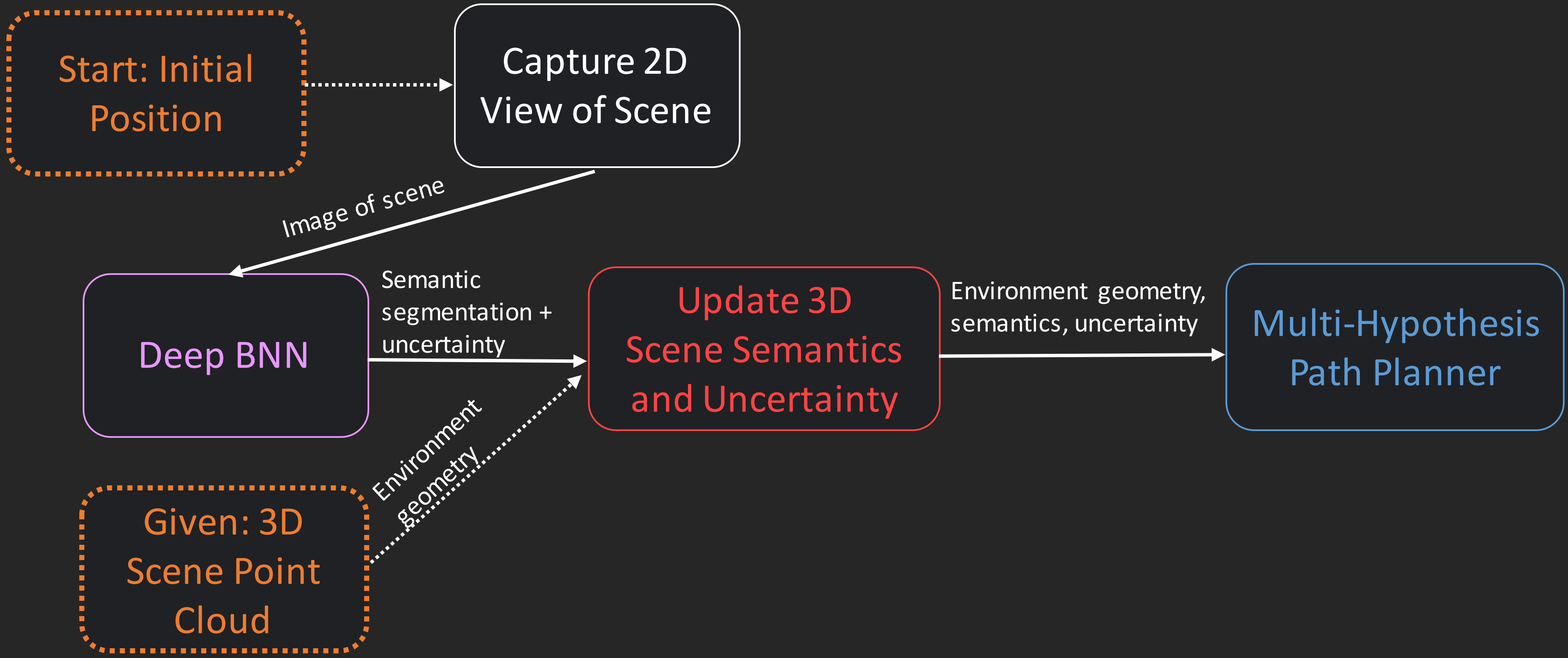

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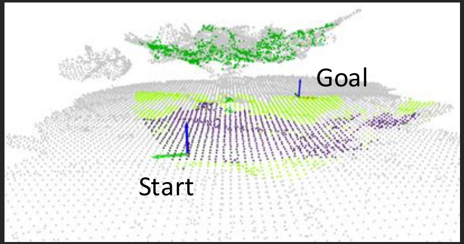


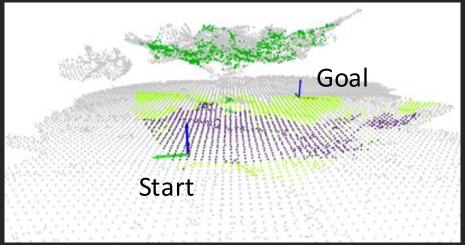
1. Semantic point cloud with uncertainties (not shown)

Update 3D Scene Semantics and Uncertainty

Environment geometry, semantics, uncertainty

Multi-Hypothesis Path Planner

DeepSemanticHPPC



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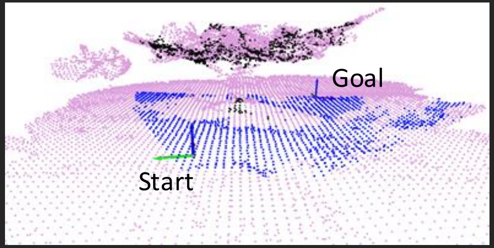
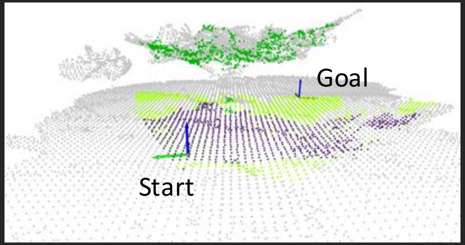


2. Safe/unsafe regions from uncertainties

Clustered Regions
- Unknown (no label or very uncertain)
- Safe (w/ uncertainty)
- Unsafe (w/ uncertainty)

Update 3D Scene Semantics and Uncertainty → Environment geometry, semantics, uncertainty → Multi-Hypothesis Path Planner

DeepSemanticHPPC



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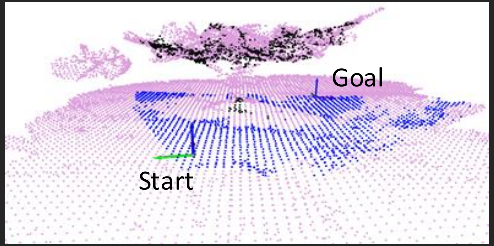

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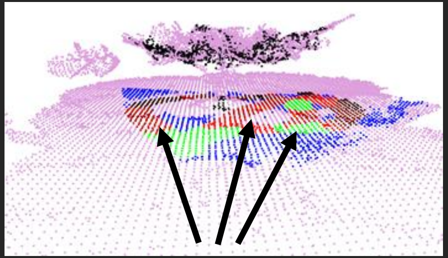


Regions for Multiple paths

3. Compute multiple hypotheses (paths) with a variant of (Krusi *et al.* 2017)

Update 3D Scene Semantics and Uncertainty

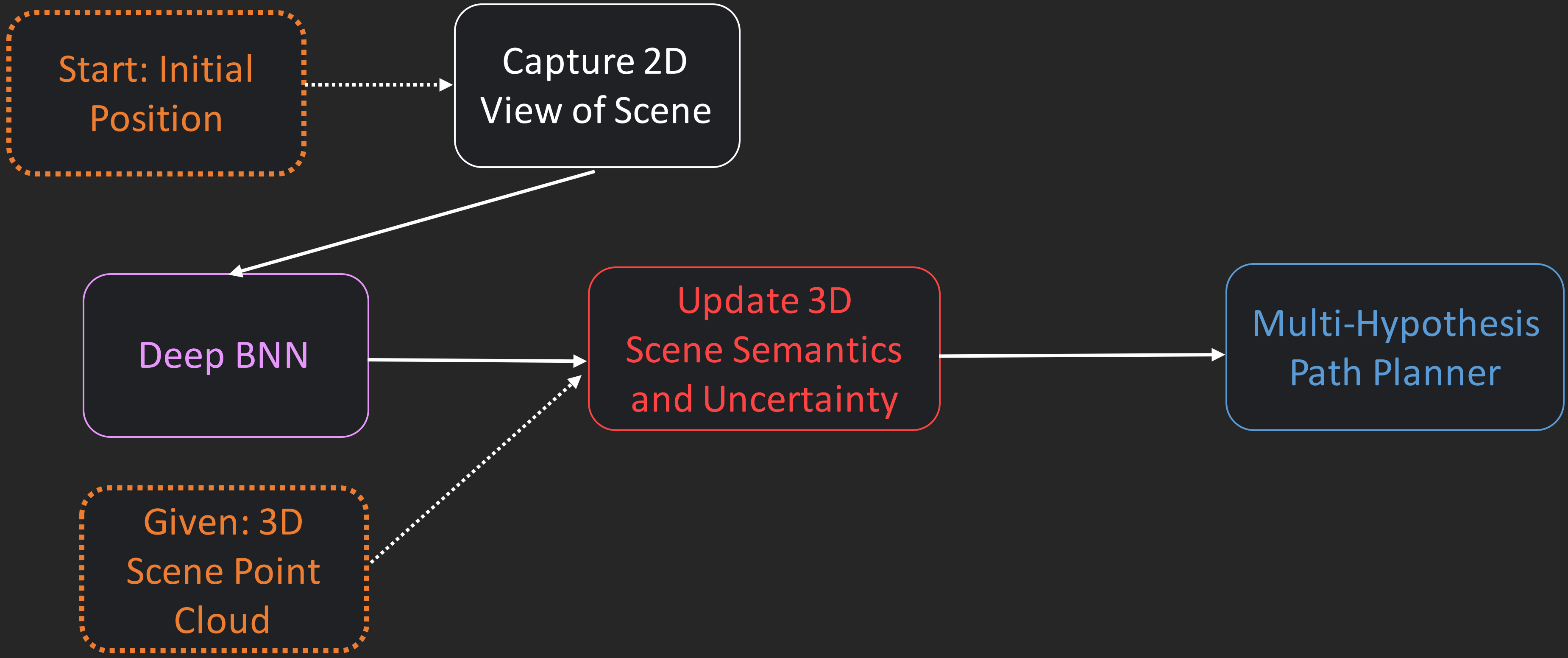
Environment geometry, semantics, uncertainty →

Multi-Hypothesis Path Planner

Path/Graph Vertices

- Unsafe (lies near unsafe or unknown cluster)
- Safe (lies in interior of safe cluster)

DeepSemanticHPPC



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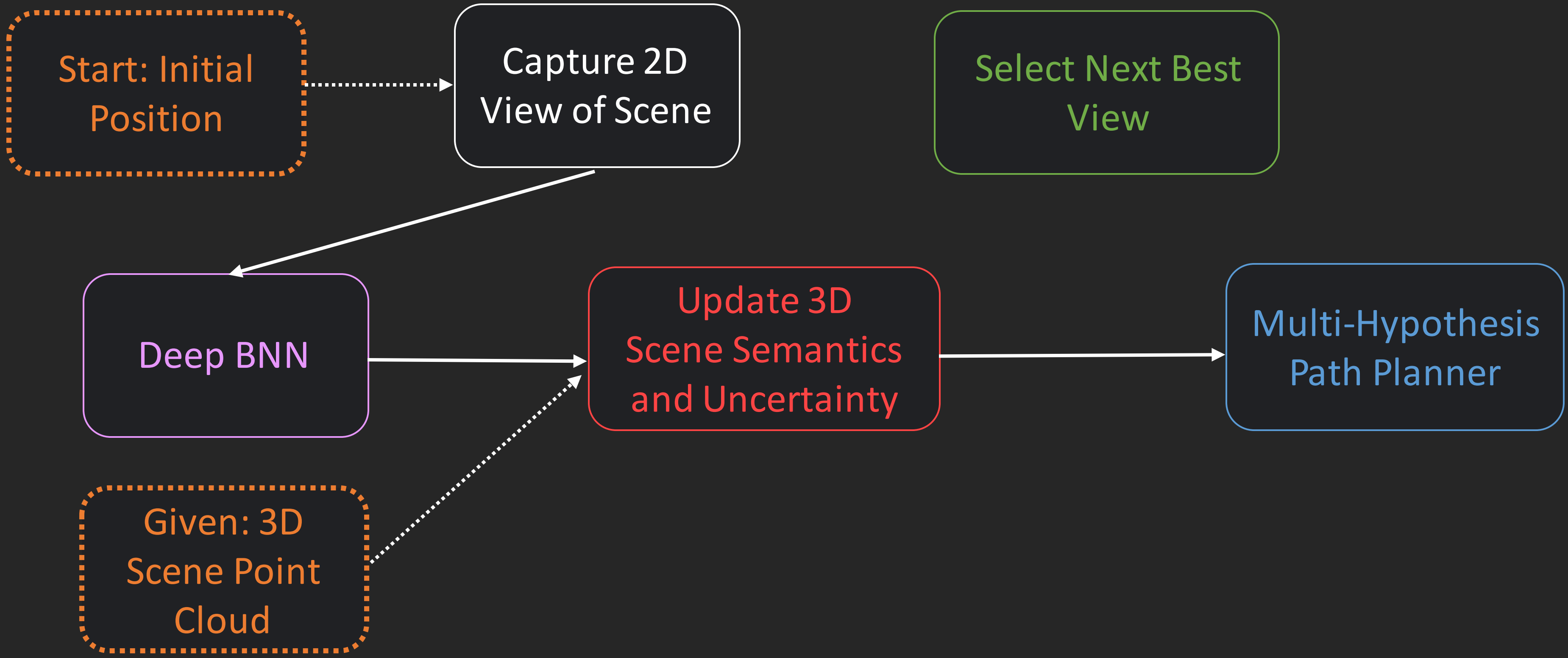

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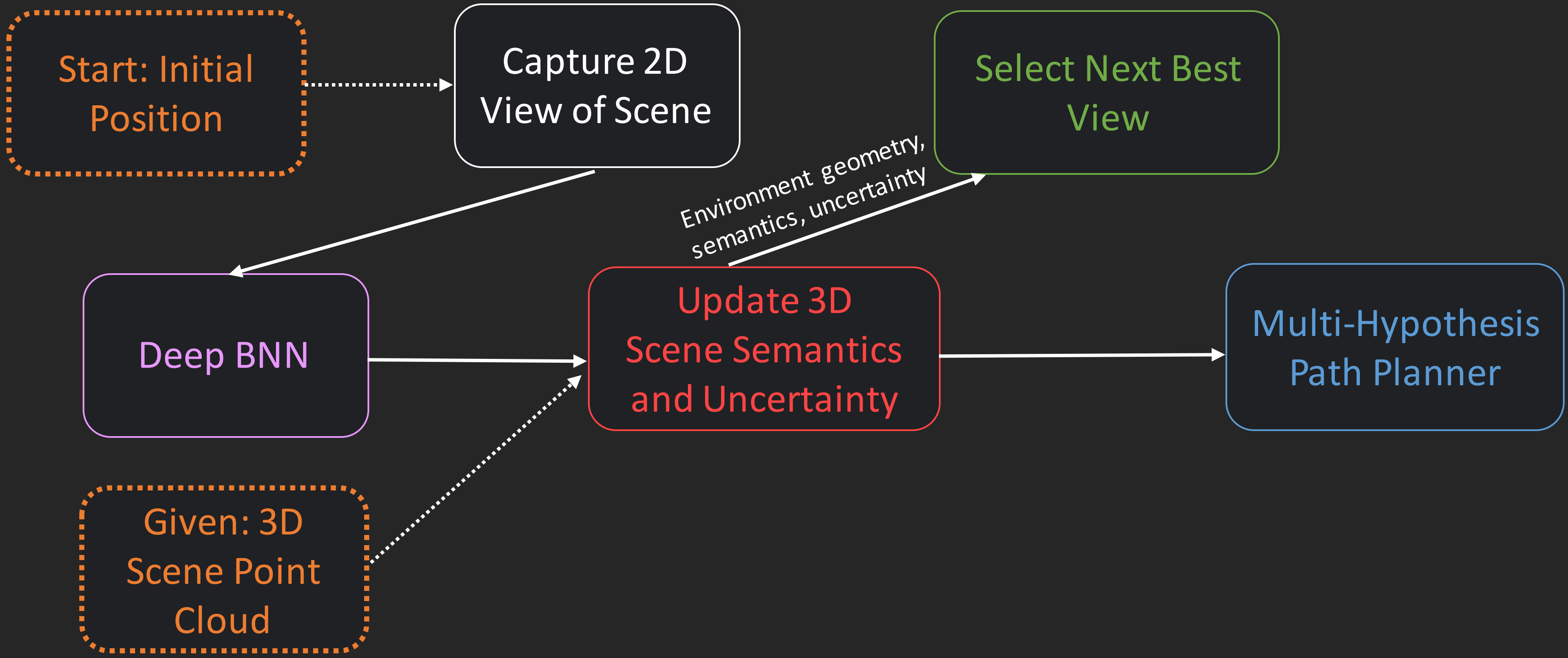

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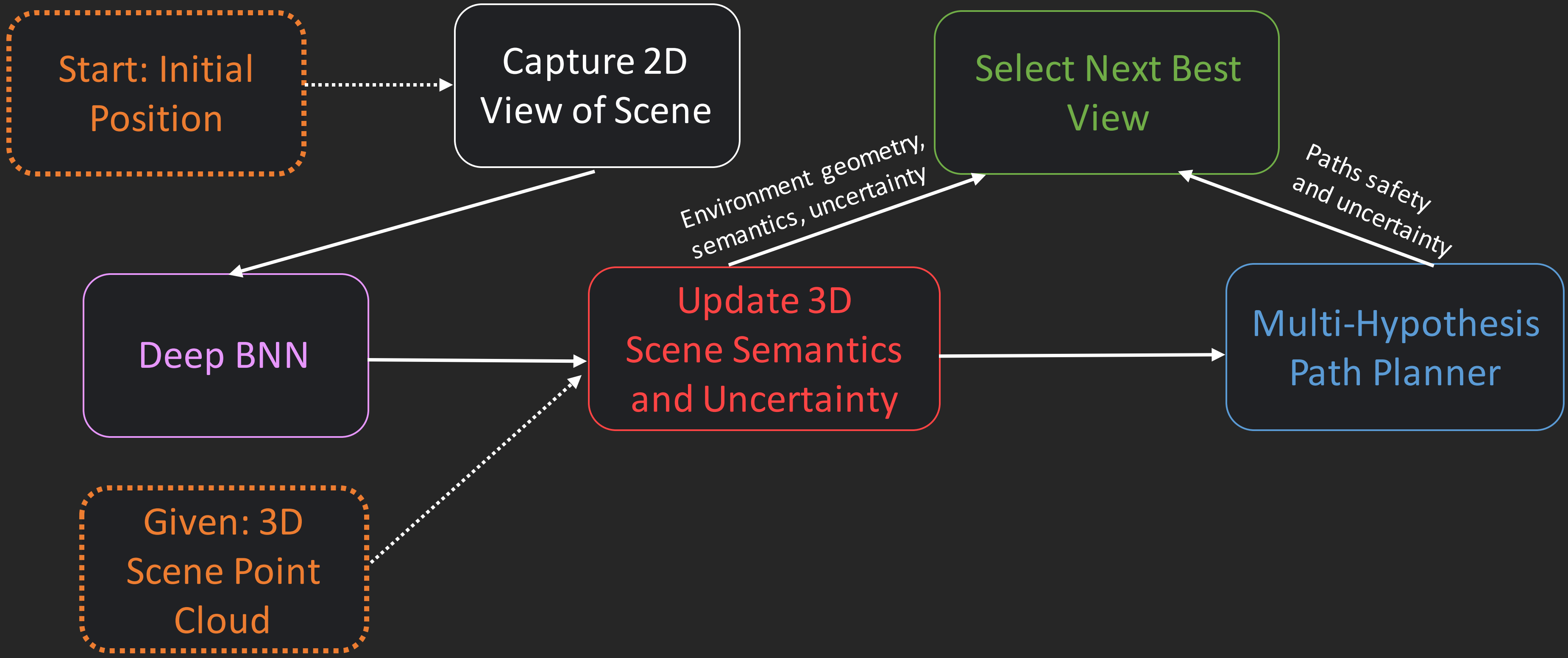

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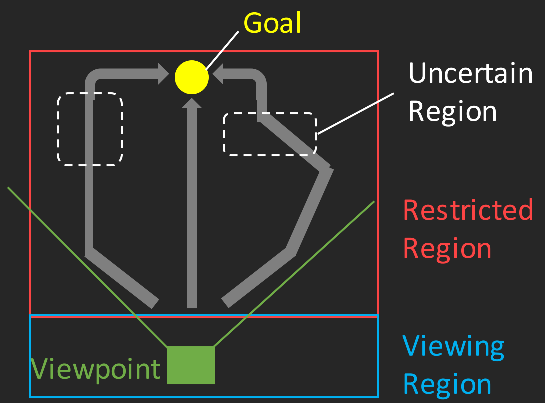

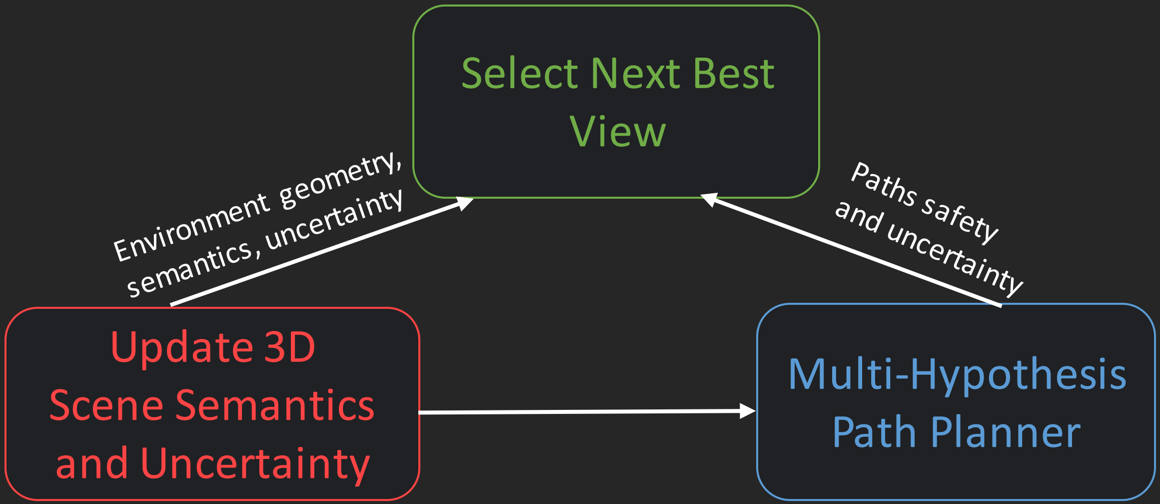

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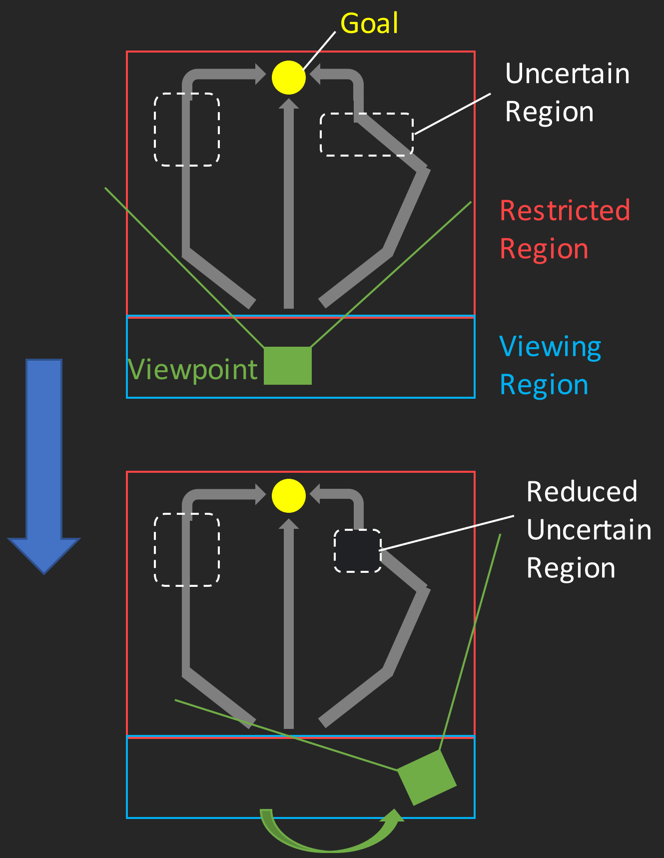
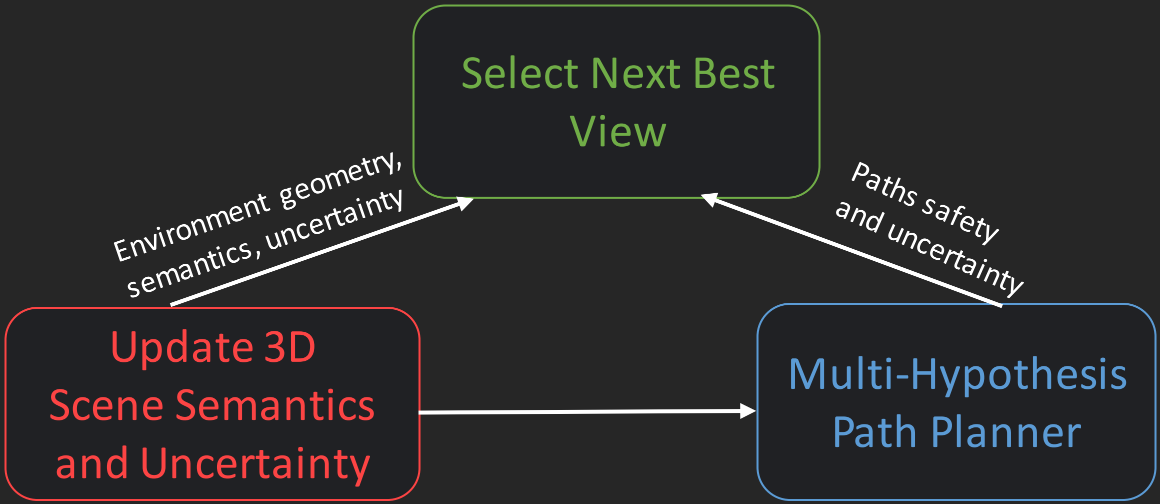
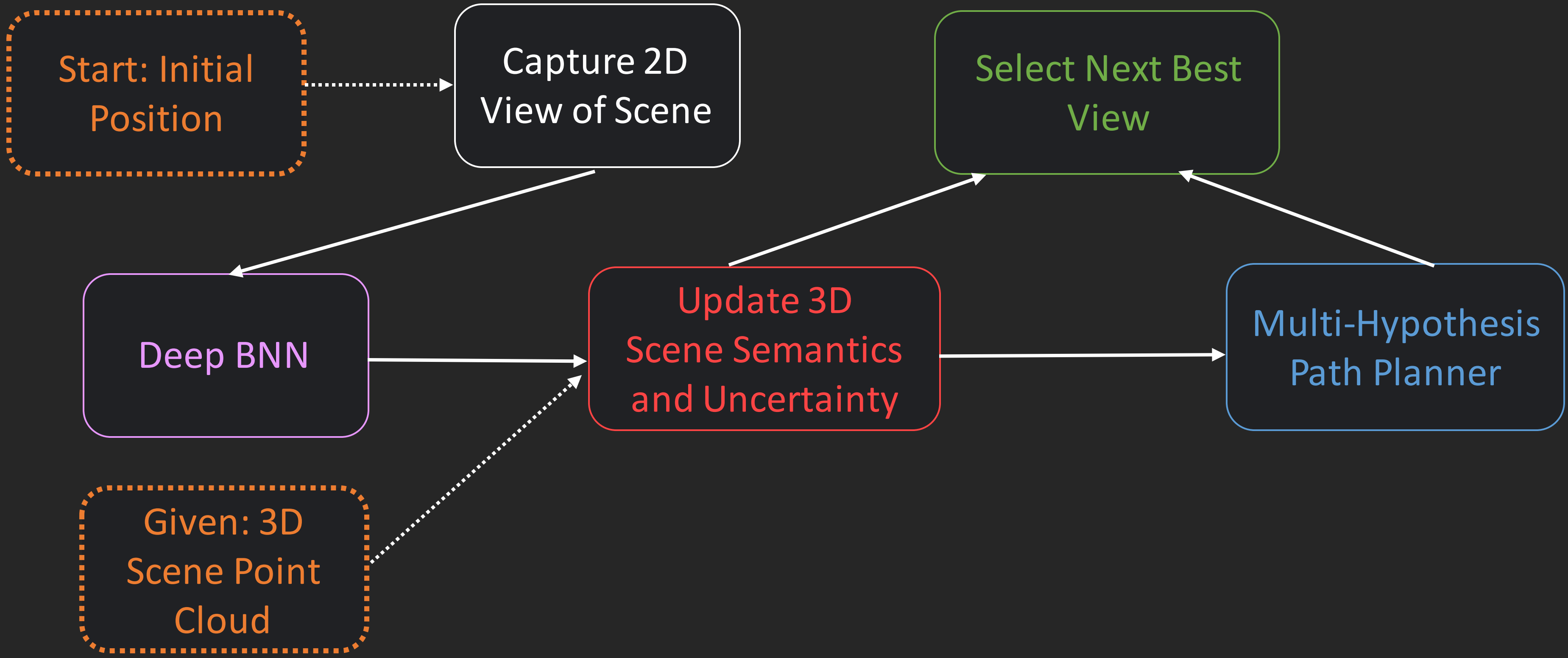


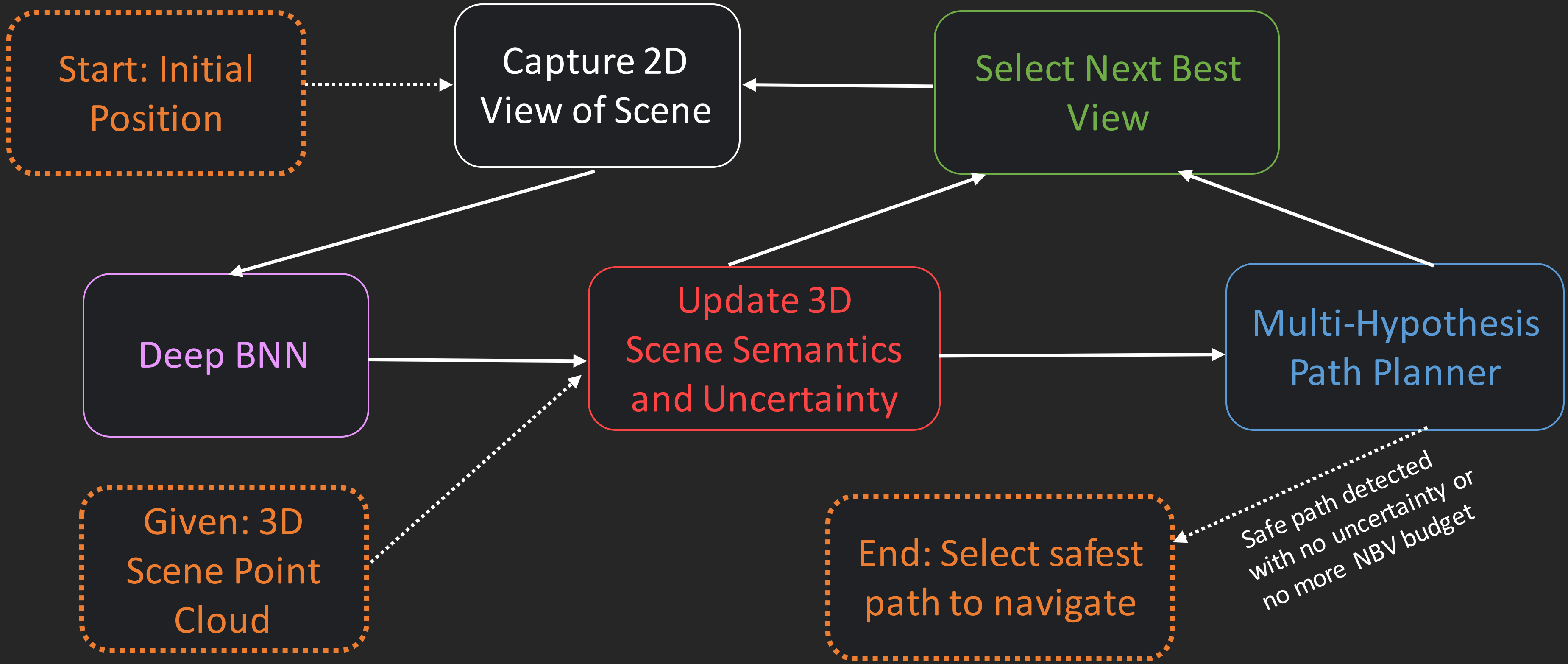


$$J\left(\mathbf{T}_{\mathrm{MV}_j}\right) = \beta_\gamma D + \beta_\gamma \gamma + \beta_{\mathrm{vis}} N_{\mathrm{vis}} + \beta_Q \bar{Q}$$

DeepSemanticHPPC



DeepSemanticHPPC Full Pipeline



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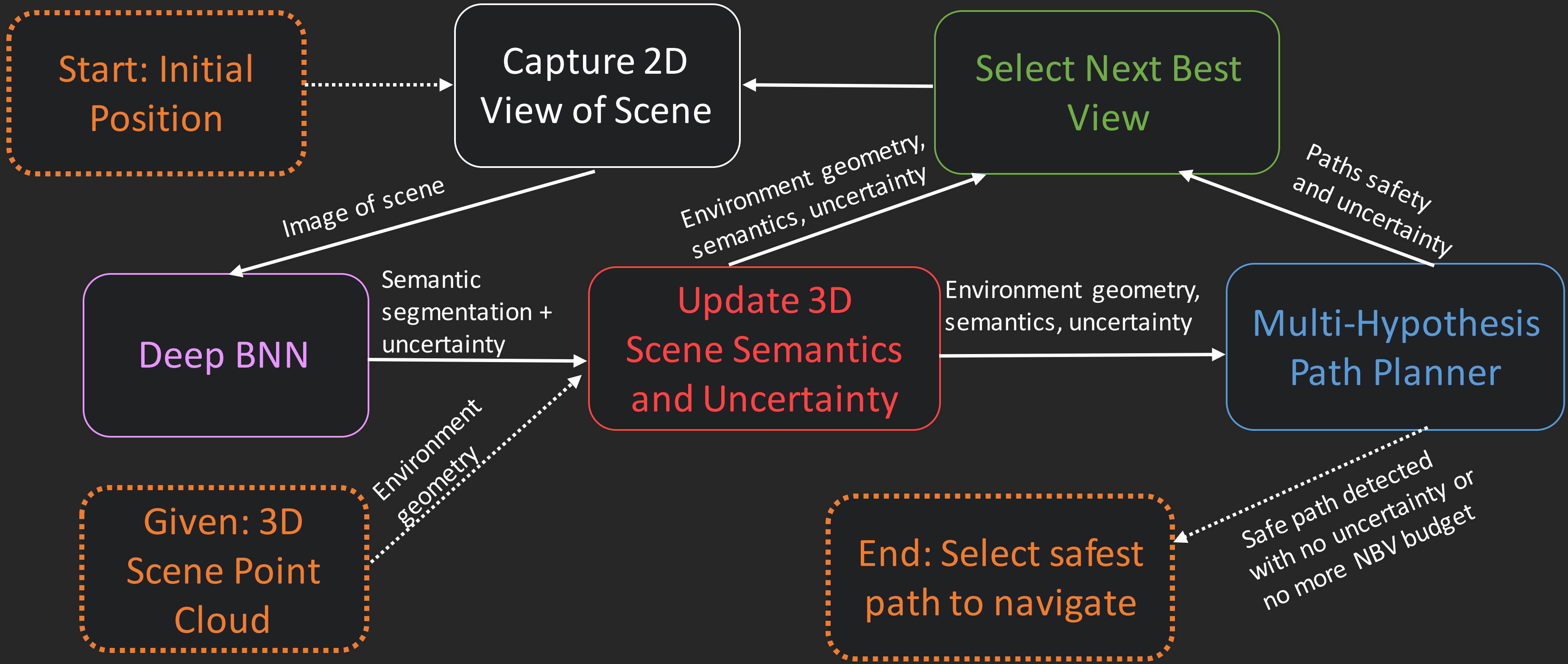


Validation

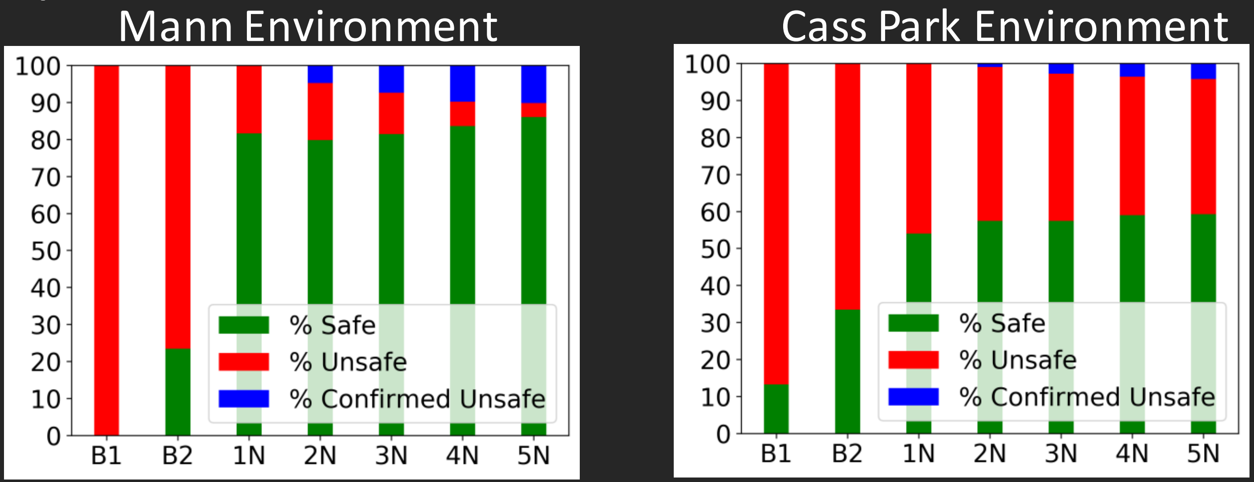
- Simulation to evaluate parameter trends
- Two real outdoor environments to evaluate real-world performance

AirSim scene
(Shah, *et al.*, (2017))

Images and reconstructions of local scenes using the ZED camera API

500 trials for each

Experimental Results: Planned Path Safety



B1: No semantics or NBV

B2: No NBV

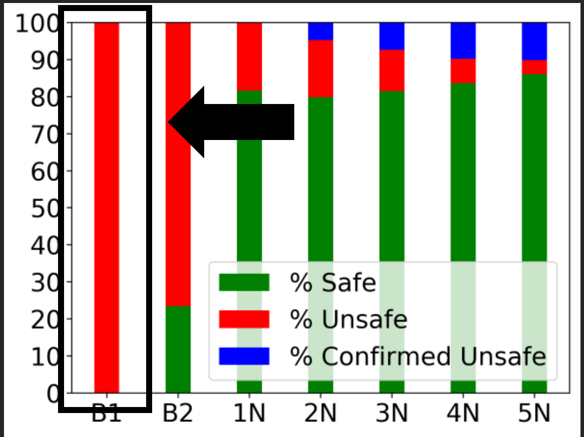
XN: Our method with X NBV

More green and blue is better!

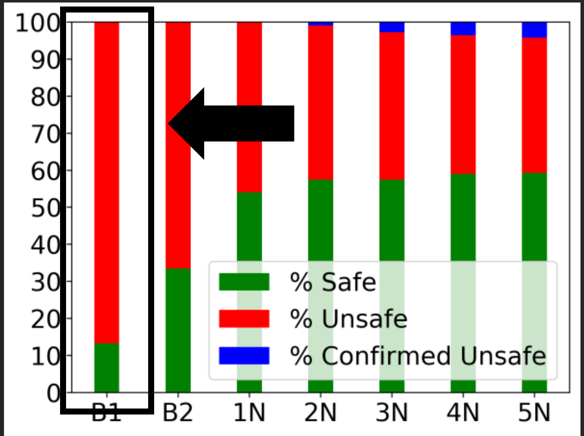
- DeepSemanticHPPC (ours) is significantly better than (Krusi *et al*. 2017) (**B1**), and even a single NBV drastically improves performance. We conclude that semantic information is critical for safe path planning.
- Our full pipeline with 5 NBVs (**5N**) achieves the best performance.

Experimental Results: Planned Path Safety

Mann Environment



Cass Park Environment



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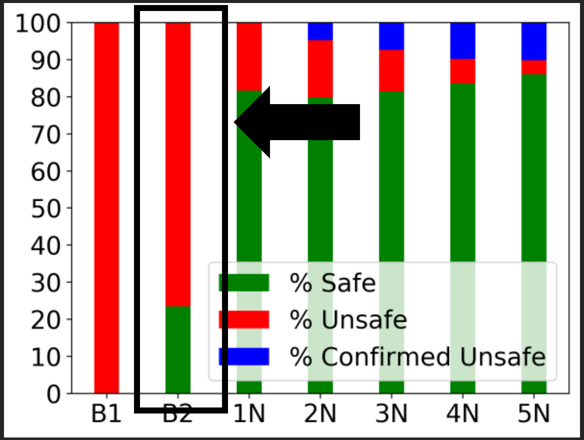

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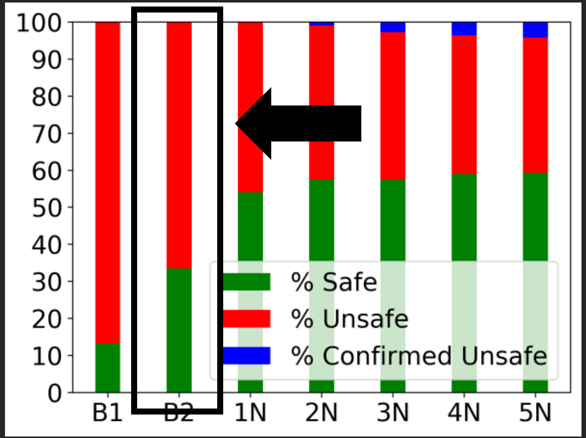

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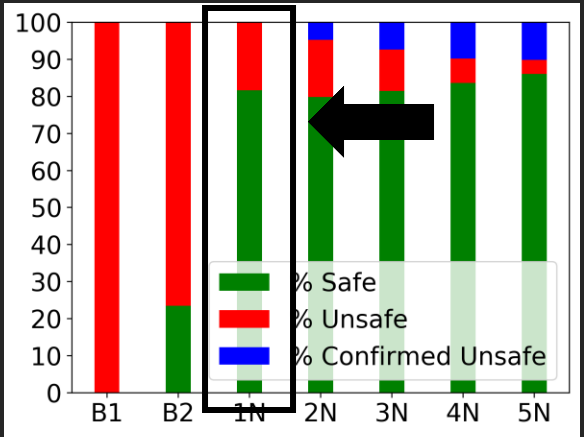

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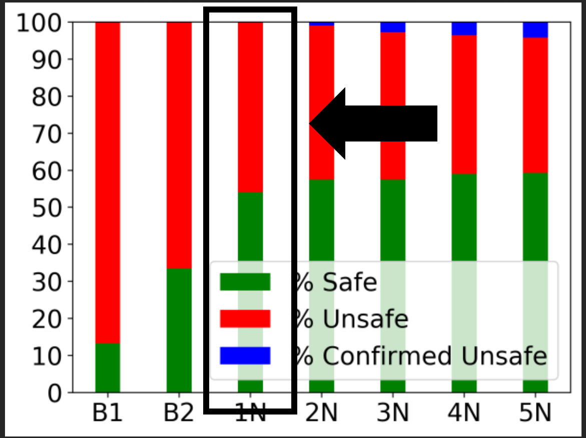

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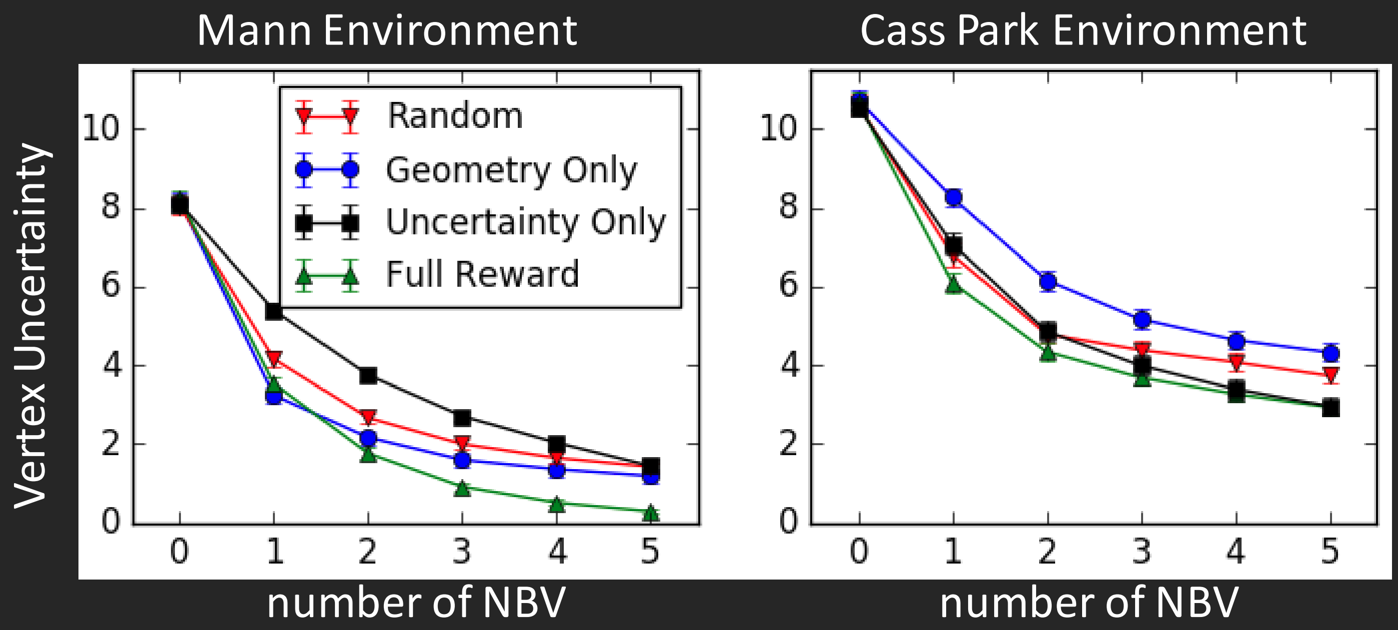
Experimental Results: Uncertainty Reduction via NBV



For both scenes, the full NBV objective function consistently achieves the lowest uncertainty with 2 or more NBVs

Summary

- Novel framework for navigation through uncertain outdoor environments
  - Reasoning about semantics and uncertainties allows safe paths to be planned.
  - Multiple path hypotheses and next best views allows measurements of the environment to reduce uncertainty and improve safety.
  - Significant improvement over baselines, even in seemingly simple real-world scenes.

Please refer to our paper for more details!

Dataset, pretrained model, and demo: https://deepsemantichppc.github.io